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Z'-Score and Logit Models for Default Prediction: An Empirical Analysis on Post-COVID M&A Transactions

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Chapter 1 – Introduction

1.1 Research Background

The global economy in recent years has been marked by profound and unexpected transformations. Structural forces such as globalization, digitalization, financial innovation, and the growing weight of emerging markets have deeply reshaped trade flows, corporate governance, and investment strategies. At the same time, geopolitical shocks, regulatory changes, and financial crises have repeatedly destabilized corporate planning, exposing the limits of traditional valuation models and highlighting the importance of robust frameworks for risk assessment.

Among these disruptive events, the outbreak of the COVID-19 pandemic stands out as a watershed moment. Far more than a health emergency, it represented an unprecedented systemic shock that abruptly affected firms' business models, altered consumer behavior, and destabilized entire supply chains. The pandemic was not only a crisis of demand but also one of liquidity and solvency. Within weeks of the first lockdowns, many companies were confronted with collapsing revenues, operational disruptions, and growing uncertainty about future financing conditions. The shock produced an exceptional asymmetry: some industries were devastated, while others experienced an acceleration of growth.

Sectors such as tourism, aviation, hospitality, and traditional brick-and-mortar retail were among the hardest hit. Airlines grounded most of their fleets, hospitality companies faced historically low occupancy rates, and retailers struggled with months of store closures. Many of these firms were heavily leveraged before the pandemic, and the sudden revenue collapse turned liquidity challenges into solvency crises. By contrast, digital platforms, e-commerce operators, pharmaceutical firms, and logistics providers registered extraordinary growth. Remote working, online shopping, and the increasing reliance on cloud services created opportunities for technology-intensive companies, while pharmaceutical and life sciences firms were placed at the center of global recovery strategies.

This divergence highlighted a fundamental element of financial analysis: resilience is unevenly distributed across industries, and systemic shocks tend to amplify rather than mitigate differences in firms' capacity to withstand stress. Companies with strong balance sheets, flexible cost structures, and scalable business models could navigate the crisis and even exploit it to reinforce their market positions. Conversely, highly leveraged or capital-intensive firms were left exposed, with little room to absorb shocks or restructure debt under deteriorating financing conditions.

In response to the crisis, governments and central banks around the world launched unprecedented measures. Monetary authorities such as the Federal Reserve and the European Central Bank introduced large-scale asset purchase programs and cut interest rates to historic lows, while fiscal authorities deployed massive support schemes for households and firms. These interventions temporarily stabilized markets and created a paradoxical situation: despite collapsing revenues, many firms avoided immediate bankruptcies thanks to abundant liquidity and cheap credit. However, this equilibrium was fragile and artificial.

When inflation accelerated in 2021 and 2022, largely due to supply chain disruptions and energy price shocks, central banks abruptly shifted their stance. Interest rates were increased at one of the fastest paces in decades, liquidity was withdrawn, and financing conditions changed dramatically. Debt servicing costs soared, refinancing risks intensified, and the structural weaknesses of highly leveraged firms became more evident. Firms that had survived thanks to government guarantees or cheap loans suddenly found themselves under renewed stress, with default probabilities rising sharply.

In this environment, merger and acquisition (M&A) activity assumed a dual character. On one side, M&A became a defensive tool: distressed companies sought acquirers capable of injecting fresh capital, restructuring their debt, or providing operational synergies needed for survival. Distress-driven transactions proliferated in industries such as aviation, retail, and oilfield services. On the other side, M&A served as an offensive strategy for stronger corporations and financial investors. Market dislocations created opportunities to acquire strategic assets at favorable valuations, consolidate fragmented industries, or diversify into new growth areas. Private equity funds, armed with record amounts of dry powder, interpreted the crisis as an opportunity to secure long-term value by acquiring temporarily weakened companies.

The coexistence of fragile and resilient targets in the post-COVID M&A landscape underscores the crucial role of financial risk assessment. For an acquirer, underestimating the vulnerability of a target can result in rapid value destruction, failed integration, and reputational damage. Conversely, missing the opportunity to acquire resilient firms at attractive valuations may entail the loss of long-term strategic advantages. Accurate assessment of financial soundness before acquisition is therefore indispensable.

Predicting default risk has become a central concern, not only for individual investors but also for the stability of the financial system as a whole. A concentration of defaults in vulnerable industries can trigger systemic effects, disrupt credit markets, reduce employment, and amplify macroeconomic volatility. This dual dimension—microeconomic, relating to the success of individual transactions, and macroeconomic, concerning systemic stability—explains why reliable default prediction models remain at the heart of financial research and practice.

Traditional tools such as Altman's Z'-Score have long provided benchmarks for assessing solvency, but their applicability in today's environment requires careful re-examination. Developed in the late 1960s for U.S. manufacturing firms, the model relies on fixed coefficients and static thresholds that may not capture the realities of a globalized, service-oriented economy. The COVID-19 crisis has further accentuated this issue, showing that extreme shocks and rapid changes in financing conditions can render historical cut-offs less effective in distinguishing between distressed and resilient companies.

Modern econometric methods, such as logistic regression, allow for more flexible treatment of data. By directly estimating the probability of default and testing the significance of explanatory variables, these models offer richer insights and can adapt to new contexts. Their application in the context of M&A is particularly relevant: acquisition decisions must often be made under uncertainty and within compressed time frames, and investors require models that combine interpretability with statistical rigor.

The pandemic, the subsequent monetary tightening, and the heterogeneous reactions of firms have therefore created a unique setting in which to revisit the problem of default prediction. Evaluating whether Altman's ratios still retain predictive validity and whether logistic regression adds tangible value is not only an academic exercise but also of immediate practical relevance for investment banks, private equity funds, and corporate acquirers seeking to navigate an increasingly volatile landscape.

1.2 Objective of the Thesis

The overarching objective of this thesis is to evaluate the effectiveness of Altman’s Z’-Score and to compare it with a logit model estimated on the same financial ratios, within the context of mergers and acquisitions (M&A) carried out in the post-COVID years.

Altman’s model, introduced in the late 1960s, has become one of the most widely recognized and enduring frameworks for bankruptcy prediction. Its appeal lies in its simplicity, transparency, and interpretability: by combining a limited set of accounting ratios into a weighted linear score, it classifies firms into safe, uncertain, or distressed categories. This feature has made it a practical tool for decades, used by practitioners, academics, and even rating agencies. Yet its very longevity raises questions about its continued relevance in modern economies characterized by service industries, intangible assets, and global capital markets.

The economic and industrial environment in which Altman’s model was developed differs profoundly from that of today. Manufacturing-based economies have transitioned toward service and knowledge-intensive sectors; firms now rely on intangible assets such as software, intellectual property, and data; and capital structures have become more complex, often including hybrid instruments and international financing. Global shocks such as the COVID-19 pandemic have exposed the limitations of models built on static thresholds, showing that resilience and vulnerability cannot always be captured by historical coefficients.

Against this backdrop, the thesis pursues a dual objective.

First, it seeks to assess the continued validity of Altman’s financial ratios—liquidity, cumulative profitability, operating profitability, leverage, and efficiency—in predicting default risk in the post-COVID environment. Testing these variables on a recent and diverse sample of M&A targets allows for an evaluation of whether they still carry explanatory power more than fifty years after their introduction, and whether their predictive capacity varies across industries and macroeconomic conditions.

Second, it aims to test the added value of a logit model, which differs from Altman’s linear discriminant in two fundamental respects: it provides probabilities rather than fixed scores, and it allows for statistical validation of each variable. By directly estimating coefficients from the dataset, logistic regression can adapt to evolving contexts and highlight which financial dimensions remain relevant today. Moreover, its probabilistic framework allows investors and acquirers to calibrate thresholds depending on their risk appetite and sectoral focus, making it more versatile in practice than Altman’s static cut-offs.

By pursuing these objectives, the thesis contributes to both theory and practice. Theoretically, it revisits one of the most influential models in corporate finance, situating it within modern empirical analysis and engaging with the broader academic literature on default prediction. It places Altman’s work in dialogue with subsequent contributions such as Ohlson’s O-Score (1980), Shumway’s hazard models (2001), and more recent machine learning approaches. Practically, it seeks to provide better tools for investment banks, private equity funds, and corporate acquirers, for whom the ability to identify fragile versus resilient targets is critical to the success of a transaction.

In this sense, the research aims to bridge the gap between tradition and innovation. It evaluates whether a model born in the 1960s can still offer valuable insights in today's environment, while also testing the contribution of a more flexible and statistically rigorous approach. The ultimate goal is to enhance the decision-making toolkit of financial practitioners, improving the quality of M&A strategies in an era of heightened uncertainty and systemic volatility.

1.3 Research Questions

The formulation of clear research questions is a critical step in structuring an academic thesis, as it ensures that the investigation is both methodologically rigorous and oriented toward meaningful objectives. In the context of corporate finance, and particularly in the high-stakes domain of mergers and acquisitions (M&A), well-defined research questions help create a direct link between theoretical foundations, empirical analysis, and practical application. This thesis builds on that principle, framing its contribution around three interconnected questions that address the continued validity of traditional bankruptcy models, the added value of modern econometric approaches, and the practical implications for decision-making in M&A transactions.

The first question asks: Are the variables included in the Z'-Score model still statistically relevant in predicting the probability of default in today's context, particularly in the aftermath of the COVID-19 crisis? This question represents the heart of the thesis. Altman's model was developed more than five decades ago in a very different economic and industrial environment, where manufacturing firms dominated and financial structures were relatively simpler. Testing whether its core financial ratios—liquidity, cumulative profitability, operating profitability, leverage, and efficiency—retain explanatory power in today's complex and globalized economy is essential to evaluating its robustness across time. By applying the Z'-Score to a recent dataset of M&A targets, the thesis explores whether the model's intuitive appeal continues to hold when exposed to modern shocks, such as the pandemic and the subsequent monetary tightening.

The second question shifts the focus from variables to methodology: Does the logit model, estimated on the same financial ratios, offer improved predictive performance compared to the traditional Z'-Score? Logistic regression differs fundamentally from Altman's discriminant approach. While the Z'-Score uses fixed coefficients and thresholds, the logit model estimates coefficients directly from the data and produces probabilities of default, which can be flexibly interpreted. The key here is whether such an approach provides more accurate, nuanced, or adaptable predictions, particularly in a dataset characterized by heterogeneity across industries and cyclical phases. If the logit model proves superior, this would not only validate the use of more advanced econometric tools but also signal a methodological evolution in default prediction research.

The third question highlights the applied dimension: What practical insights can be drawn from the results for stakeholders involved in M&A activity? While theory and statistical validation are important, the true relevance of default prediction models lies in their contribution to real-world decisions. M&A transactions are strategic moves with significant financial and reputational consequences. For investment bankers, analysts, private equity funds, and corporate managers, the ability to correctly assess the financial stability of a target can be the difference between a successful acquisition and a costly failure. This research question ensures that the analysis remains grounded in practice and that its findings are not only academically robust but also operationally useful in guiding due diligence and risk management.

Taken together, these three research questions provide a coherent framework for the thesis. They ensure that the work is not an abstract methodological exercise but a structured investigation that bridges theory, empirical evidence, and practice. By linking traditional models with modern econometric approaches and applying them to the post-COVID M&A landscape, the thesis contributes simultaneously to scholarly debates on default prediction and to the strategic toolkit of financial practitioners.

1.4 Methodology

To address the research questions outlined above, this thesis adopts a structured empirical methodology that integrates descriptive financial analysis with econometric modeling. The approach is designed to achieve a balance between interpretability, statistical rigor, and practical applicability, ensuring that the results provide both academic insights and tangible value for M&A practitioners.

The first step involves constructing the dataset. The empirical sample includes approximately one hundred M&A transactions completed or announced between 2018 and 2023, with a deliberate emphasis on the post-COVID years. This timeframe is particularly significant, as it captures the immediate disruptions caused by the pandemic, the period of extraordinary monetary accommodation, and the subsequent phase of sharp monetary tightening. Only deals with a minimum value of five million U.S. dollars were included, and transactions with incomplete financial information were excluded to ensure comparability. For each target firm, financial statements from the year immediately preceding the acquisition were collected from reliable sources such as Orbis, Yahoo Finance, and official filings like annual reports and 10-K statements. This guarantees transparency and replicability, two critical pillars of empirical research.

The second step is the calculation of Altman's Z'-Score for each firm in the dataset. The model combines five accounting ratios into a single score that classifies companies into distress, grey, or safe zones. Beyond computing these scores, the analysis presents descriptive statistics—averages, medians, standard deviations, and distributions across years and sectors. This enables the identification of patterns of resilience and fragility across industries and macroeconomic phases. To strengthen the analysis, case studies of extreme outliers are included, showing how the Z'-Score aligns with real-world events such as bankruptcies, restructurings, or unusually strong financial performance.

The third step introduces the logit model, estimated using the same five financial ratios that form the basis of Altman's Z'-Score. Logistic regression allows for a more flexible framework: it tests the statistical significance of each explanatory variable, provides estimated coefficients that reflect the specific dataset, and produces firm-specific probabilities of default. This represents a significant departure from the deterministic nature of the Z'-Score, where outcomes are tied to fixed historical thresholds. The logit model makes it possible to capture nuances in the data and to adapt interpretations according to sectoral or investor-specific contexts. Its predictive performance is evaluated through a set of metrics, including classification accuracy, the likelihood-ratio test, and McFadden's pseudo-R^2, all of which are well-established in econometric literature.

The fourth step consists of a comparative evaluation of the two models. While the Z'-Score offers the advantage of simplicity and long-standing recognition, the logit model introduces statistical rigor and greater flexibility. The comparison is conducted not only in terms of predictive accuracy but also with regard to interpretability and applicability. For instance, the Z'-Score provides an immediate and easily communicable classification scheme, whereas the logit model allows for probability-based rankings that can be tailored to different risk appetites. This comparative exercise highlights the complementarities of the two approaches rather than treating them as substitutes.

Finally, the methodology incorporates validation techniques to ensure the robustness of the findings. Building on best practices in empirical research, additional checks such as the ROC–AUC and classification matrices are used to confirm the predictive quality of the logit model. These complementary measures consolidate the reliability of the results and reinforce the conclusions drawn in later chapters.

Overall, the methodological framework adopted in this thesis is deliberately comprehensive. By combining descriptive statistics, case analysis, econometric estimation, and validation metrics, it provides a well-rounded perspective on the problem of default prediction. The dual focus on Altman's Z'-Score and the logit model reflects a conscious attempt to bridge historical interpretability with modern flexibility, thereby enhancing financial risk assessment in the context of mergers and acquisitions.

1.5 Structure of the Thesis

The thesis is organized into five main chapters, each designed to guide the reader through a logical progression that moves from the general context to the specific empirical investigation, and finally to the conclusions and implications. The structure reflects both academic rigor and practical orientation, ensuring that the discussion remains coherent, accessible, and directly tied to the research objectives.

Chapter 1 – Introduction serves as the foundation of the work. It begins by situating the research within the broader economic and financial landscape, highlighting how structural trends such as globalization, digitalization, and the rise of emerging markets have reshaped corporate solvency and investment strategies. Particular emphasis is placed on the disruptive effects of the COVID-19 pandemic, which acted as a stress test for firms across industries and reshaped the dynamics of M&A activity. The chapter then clarifies the objectives of the study, formulates the guiding research questions, and presents the methodological framework to be employed. By outlining the rationale, scope, and intended contribution, the introduction establishes a clear roadmap for the reader and sets the stage for the more technical discussions that follow.

Chapter 2 – Literature Review provides the theoretical underpinnings of the thesis. It first presents Altman's Z'-Score model, discussing its origins, structure, and historical significance as one of the most influential tools in bankruptcy prediction. The review then moves to the evolution of the model, highlighting its limitations in light of today's service-oriented and globalized economy. Particular attention is given to recent academic contributions that critique the static nature of

Altman's coefficients and thresholds. The chapter then introduces logistic regression as a modern alternative, capable of producing probabilities of default and testing the significance of explanatory variables. Finally, it reviews applications of both the Z'-Score and the logit model in the specific context of M&A, thereby situating this thesis within an ongoing scholarly debate on how best to predict default risk in high-stakes financial transactions.

Chapter 3 – Data and Methodology describes the empirical framework. It details the construction of the dataset, which consists of approximately one hundred M&A transactions completed or announced between 2018 and 2023, with an emphasis on the post-COVID period. The chapter explains the criteria for sample selection, the financial ratios derived from company accounts, and the sources of information used, such as Orbis, Yahoo Finance, and official filings. It then describes the computation of Altman's Z'-Score and the estimation of the logit model, clarifying the methodological choices that enable a direct comparison of the two approaches. Additionally, the chapter introduces the evaluation metrics—classification accuracy, the likelihood-ratio test, pseudo-R^2, and ROC–AUC—that serve as benchmarks for assessing predictive performance. By doing so, it establishes a clear methodological foundation for the empirical results.

Chapter 4 – Empirical Results represents the analytical core of the thesis. It begins with a descriptive overview of the sample, including temporal trends and distributions of Z'-Scores across years and industries. A sectoral breakdown is then provided, highlighting how fragility and resilience vary systematically across different industries, from cyclical sectors such as automotive and energy to defensive sectors such as healthcare and technology. The analysis continues with case studies of outliers, focusing on companies at the extremes of financial health, in order to illustrate the discriminatory power of the Z'-Score. The chapter then presents the logit regression results, emphasizing the statistical significance of profitability and leverage as drivers of default risk, and commenting on the weaker performance of liquidity and efficiency ratios. It proceeds with a comparative evaluation of the Z'-Score and logit approaches, underlining their complementarities rather than treating them as substitutes. Finally, robustness checks and additional validation techniques—such as sub-sample estimations, ROC–AUC, and classification matrices—are introduced to consolidate the reliability of the results and confirm the stability of the main conclusions.

Chapter 5 – Conclusions integrates and reflects on the findings of the research. It first summarizes the key empirical results, emphasizing the enduring relevance of Altman's ratios while also demonstrating the superior flexibility and statistical rigor of the logit model. The chapter then explores the theoretical implications, showing how profitability and leverage remain fundamental predictors of solvency, while liquidity and efficiency appear less relevant in today's context. The practical implications are also discussed, particularly for M&A practitioners, highlighting how the two models can be applied in complementary ways at different stages of the acquisition process. The chapter then acknowledges the main limitations of the study—such as sample size, sectoral imbalances, and methodological simplifications—and proposes directions for future research, including the integration of macroeconomic and qualitative variables, as well as the application of advanced machine learning techniques. By closing with both a reflection on achievements and a call for innovation, this chapter positions the thesis as a contribution to an ongoing dialogue in both academic and professional circles.

In sum, the five chapters are designed to provide a coherent narrative that moves logically from background and motivation, through theoretical and methodological foundations, to empirical evidence and final reflections. This structure ensures that the thesis not only maintains academic rigor but also generates practical insights for financial practitioners engaged in M&A, bridging the gap between tradition and innovation in the field of default prediction.

Chapter 2 – Literature Review

2.1 Introduction to Corporate Default Prediction

The prediction of corporate default has been a central topic in corporate finance and risk management for more than half a century. Anticipating whether a company is likely to experience financial distress or bankruptcy is crucial for a wide range of stakeholders, including creditors, investors, employees, and regulators. The collapse of a firm not only generates direct costs for shareholders and bondholders but can also disrupt supply chains, reduce employment, and in some cases pose risks to the stability of the financial system. For these reasons, the development of models capable of providing early warning signals of default has attracted sustained attention from both academics and practitioners.

The first systematic attempts to predict corporate failure date back to the 1960s. Early contributions, such as Beaver (1966), focused on univariate ratio analysis, testing the ability of individual financial ratios—such as cash flow to total debt or net income to total assets—to discriminate between failed and non-failed firms. While pioneering, this approach was soon criticized for its limitations: it ignored the joint effect of multiple financial dimensions and often produced results that were sensitive to sample selection.

A major methodological advance came with Altman (1968), who introduced multivariate discriminant analysis to the problem of default prediction. His model, which combined several accounting ratios into a single score—the now famous Z'-Score—represented a breakthrough in the field. By simultaneously incorporating measures of liquidity, cumulative profitability, operating efficiency, leverage, and asset turnover, Altman demonstrated that corporate failure could be predicted with significantly higher accuracy than through univariate approaches. The Z'-Score quickly became a benchmark in both research and practice, widely adopted by banks, investors, and credit rating agencies as a tool for assessing creditworthiness.

The importance of default prediction, however, extends beyond the immediate interests of lenders and investors. Regulatory authorities rely on early warning models to monitor the health of financial institutions and to prevent systemic crises. Credit rating agencies incorporate insights from bankruptcy prediction models when assigning ratings, which in turn influence the cost of capital for firms. Even policymakers use default indicators to evaluate corporate vulnerability during periods of macroeconomic stress, such as recessions, financial crises, or pandemics. The systemic dimension of corporate distress highlights the need for reliable and continuously updated prediction tools.

In the context of mergers and acquisitions (M&A), the relevance of default prediction becomes even more pronounced. Acquirers must evaluate not only the strategic and operational fit of a target firm but also its financial resilience. An inaccurate assessment of solvency may result in acquiring companies that subsequently default or require costly restructuring, leading to significant value destruction. Conversely, identifying financially solid targets can provide acquirers with opportunities to consolidate market share, expand into new sectors, or secure competitive advantages. The quality of financial risk assessment is therefore a decisive factor in determining the success or failure of M&A transactions.

The challenge has become particularly acute in the post-COVID era. The pandemic left many firms in a fragile state, with weakened balance sheets and increased leverage, making it more difficult to distinguish between temporary shocks and structural weaknesses. At the same time, monetary tightening in the aftermath of the crisis has raised the cost of debt, further stressing vulnerable firms. In such a context, models that can effectively predict default are essential for guiding capital allocation and ensuring that M&A decisions are grounded in a robust assessment of financial health.

In sum, corporate default prediction has evolved from early univariate studies to more sophisticated multivariate and probabilistic models, reflecting the growing complexity of modern firms and financial systems. Its relevance spans multiple domains, from investment decisions to regulatory oversight and is particularly critical in high-stakes environments such as M&A. The next sections of this chapter review the evolution of Altman's Z'-Score, its subsequent refinements and limitations, and the growing role of logistic regression as an alternative approach to predicting corporate failure.

2.2 Altman's Z'-Score Model: Structure and Use

Among the various models developed to predict corporate insolvency, Altman's Z'-Score remains one of the most influential and enduring. Introduced in 1968 by Edward I. Altman, the model represented a major methodological breakthrough in the field of financial distress prediction. Unlike earlier univariate approaches, which examined single ratios in isolation, Altman's contribution lay in combining multiple accounting variables into a multivariate discriminant function, thereby capturing the joint explanatory power of several dimensions of corporate performance.

The original model was designed for publicly traded manufacturing firms in the United States, reflecting the industrial composition of the economy at the time. Altman selected five financial ratios based on both theoretical considerations and empirical testing, each representing a different aspect of corporate health:

- Working Capital / Total Assets (WC/TA) → a measure of liquidity, capturing the firm's ability to meet short-term obligations with available current assets.
- Retained Earnings / Total Assets (RE/TA) → a proxy for cumulative profitability and corporate maturity, indicating how much of the firm's assets are financed through internally generated funds rather than external debt.
- Earnings Before Interest and Taxes / Total Assets (EBIT/TA) → a measure of operating efficiency, assessing the firm's ability to generate operating income relative to its asset base.
- Market Value of Equity / Total Liabilities (MVE/TL) → an indicator of leverage and solvency from a market perspective, linking the market capitalization of equity to the book value of liabilities.
- Sales / Total Assets (S/TA) → a measure of asset turnover, reflecting the efficiency with which the company uses its assets to generate revenues.

These ratios were weighted according to coefficients derived from discriminant analysis, producing a single composite score—the Z'-Score—that could classify firms into zones of safety, uncertainty, or distress. Empirical tests conducted on Altman's original sample showed accuracy rates exceeding 90% in distinguishing bankrupt from non-bankrupt firms, a level of predictive performance that was remarkable for its time and that cemented the model's reputation.

Over the years, Altman introduced several refinements and adaptations to broaden the model's applicability:

- The Z'-Score (1983) was adapted for private firms, replacing the market value of equity with book value of equity, since private companies often lack reliable market capitalization data.
- The Z''-Score (1995) was developed to extend the model to non-manufacturing firms and emerging markets, adjusting both the coefficients and the interpretation of certain variables.

These extensions increased the model's relevance and ensured its diffusion across different geographies and industries. By the 1990s, the Z'-Score and its variants had become standard tools not only in academic studies but also in credit risk management, corporate banking, and investment analysis. Rating agencies, banks, and regulators adopted it as part of their early warning systems, appreciating its interpretability and relatively low data requirements compared to more complex econometric or market-based models.

However, despite its success, the Z'-Score is not without limitations. The model is inherently static and linear: it assumes fixed relationships between financial ratios and default risk, relationships that were estimated in a specific historical and industrial context. The globalized and highly volatile financial environment of today differs significantly from the U.S. manufacturing sector of the late 1960s. For example, the growing importance of intangible assets, off-balance sheet financing, and sector-specific dynamics may not be adequately captured by the original ratios. Moreover, the model does not incorporate qualitative factors such as corporate governance, managerial quality, or industry-specific risks, nor does it account for macroeconomic conditions such as monetary policy shifts or systemic crises.

Another limitation lies in the reliance on fixed thresholds to classify firms into safe, grey, and distress zones. While convenient, these cut-offs are based on historical samples and may not reflect the realities of different industries, geographies, or time periods. As a result, the model's predictive accuracy may deteriorate in contexts far removed from those in which it was originally developed.

Nevertheless, the Z'-Score continues to hold a prominent place in the literature and in practice. Its enduring popularity is explained by its simplicity, transparency, and interpretability: the model requires only standard accounting data, it is easy to compute, and its meaning is intuitive even for non-specialists. For these reasons, it remains widely used as a first-pass screening tool, often complemented by more advanced methods in professional applications.

Overall, Altman's Z'-Score occupies a unique position in the history of default prediction models. It represents both a methodological innovation and a benchmark against which subsequent models are measured. Its strengths—simplicity, empirical grounding, and interpretability—are balanced by limitations that stem from its historical origins and static nature. The next section will explore how more recent literature has evaluated the Z'-Score, questioning its universal validity and proposing complementary or alternative approaches better suited to contemporary financial environments.

2.3 Recent Literature on the Z'-Score Model: Evolutions and Limitations

Over the past two decades, a vast body of literature has revisited Altman's Z'-Score model in light of the structural transformations of the global economy, the recurrence of financial crises, and the increasing complexity of corporate balance sheets. While the framework has retained extraordinary diffusion in both academic and professional contexts, recent studies have questioned the universal validity of its coefficients, the stability of its predictive thresholds, and the adequacy of its variables in capturing the financial fragility of modern firms.

One of the most frequently debated issues concerns the reliability of the traditional cut-offs used to classify firms into distress, grey, and safe zones. The thresholds of 1.23 and 2.90 were calibrated on a sample of U.S. manufacturing firms in the 1960s. Subsequent empirical evidence shows that these values often fail to generalize across different industries, geographies, and macroeconomic conditions. For example, service-based and asset-light firms—such as digital platforms or consulting companies—naturally report lower sales-to-assets ratios, which could incorrectly push them into the distress zone even when they are structurally solid. In contrast, firms operating in emerging markets frequently display higher leverage due to institutional factors and banking-based financial systems. In such cases, applying Altman's fixed thresholds risks systematic misclassification, suggesting the need for context-specific recalibration rather than reliance on universal standards.

Another major strand of critique relates to the changing relevance of the underlying variables. Empirical contributions have shown that while measures of profitability (EBIT/TA, RE/TA) and leverage (MVE/TL) retain strong explanatory power across contexts, the predictive content of Sales-to-Assets (S/TA) has diminished substantially. The original model was designed in an industrial economy dominated by tangible assets and physical production, where turnover efficiency was critical. In today's service-driven and digital economy, corporate value creation often depends on intangible assets, intellectual property, and knowledge capital—dimensions that are not adequately captured by asset turnover ratios. Similarly, working capital ratios may be less meaningful for technology-based firms with negative working capital models but robust profitability.

The sensitivity of the Z'-Score to economic crises has also received increasing attention. Studies conducted after the 2008 global financial crisis demonstrated that the model's predictive accuracy declined sharply during periods of systemic stress. Defaults triggered by liquidity shortages, contagion effects, or sudden credit market freezes were not fully captured by accounting-based indicators. More recently, analyses of the COVID-19 shock confirmed this limitation. During the pandemic, many firms registered collapsing revenues and deteriorating ratios due to temporary lockdowns, while their long-term solvency remained intact. The Z'-Score tended to overstate default risk in such cases, highlighting its vulnerability in non-linear environments where extraordinary shocks distort financial statements.

In response to these issues, scholars have explored ways to integrate or recalibrate the model. Several approaches have emerged:

- Logistic regression models allow for formal testing of variable significance and the estimation of probabilities of default rather than deterministic scores.
- Hazard and survival models incorporate time-to-default, extending the predictive horizon beyond static classification.
- Machine learning algorithms (random forests, neural networks, support vector machines) have been applied to large datasets to capture non-linear relationships and complex interactions overlooked by linear discriminant analysis.

These innovations generally do not aim to replace the Z'-Score entirely. Instead, they emphasize its continued usefulness as an intuitive benchmark while stressing the need for integration with more flexible, data-driven approaches. A recurring theme in the literature is that Altman's ratios still contain valuable information, particularly those linked to profitability and leverage, but their predictive power is uneven and context-dependent.

The consensus emerging from recent contributions is therefore nuanced: the Z'-Score remains a valuable starting point but cannot be applied mechanically. Its continued use requires sectoral adaptation, geographical recalibration, and complementary econometric validation. This critical reassessment sets the stage for the discussion of logistic regression as both an alternative and a complement, providing a framework that combines the interpretability of Altman's model with the statistical rigor and flexibility required in contemporary credit risk analysis.

2.4 Logistic Regression in Default Prediction

Among the econometric techniques that have gained prominence in credit risk modeling, logistic regression (logit) has emerged as one of the most widely used and enduring. Its suitability for binary classification problems makes it particularly well-adapted to default prediction, where the outcome of interest is dichotomous: a firm either defaults (1) or remains solvent (0). The popularity of logistic regression derives from its ability to balance statistical rigor, interpretability, and practical applicability, making it useful for both academics and practitioners in credit analysis, banking, and M&A.

The key advantage of the logit framework over Altman's Z'-Score is that it directly estimates the probability of default rather than producing a composite score to be compared against fixed thresholds. This probabilistic output allows for much richer interpretation. Different stakeholders can set their own cut-offs depending on context and risk appetite: a conservative regulator may treat any firm with more than a 10% probability of default as risky, while a private equity fund specialized in turnarounds may tolerate probabilities above 40%. By providing probabilities instead of rigid categories, the logit model offers a more flexible and customizable tool for decision-making.

From a methodological perspective, logistic regression is based on the logistic function, which transforms a linear combination of explanatory variables into probabilities bounded between 0 and 1. This functional form is particularly suitable for default prediction: it guarantees meaningful outputs, avoids negative or unbounded probabilities, and reflects the idea that the marginal effect of each variable diminishes as the probability approaches extreme values.

Logistic regression introduces several innovations compared to linear discriminant models such as the Z'-Score:

- It allows for statistical testing of explanatory variables, enabling researchers to identify which ratios are truly significant in predicting default. This contrasts with Altman's fixed weights, which were derived historically and are not dataset-specific.
- It is easily re-estimated when new data become available, ensuring adaptability across different industries, geographies, and time periods.
- It produces continuous, probability-based outputs, which provide more nuanced risk assessments than categorical classifications.

Over time, the logit framework has been expanded to address real-world complexities. Probit models use a cumulative normal distribution instead of a logistic one, offering slightly different statistical properties but similar results. Survival analysis incorporates the temporal dimension, estimating not just the probability of default but also the expected time until default, which is particularly relevant for long-term credit instruments. Panel logit models exploit repeated firm-level observations across multiple years, allowing researchers to account for unobserved heterogeneity and improving robustness. These extensions highlight the adaptability of logistic regression to diverse empirical settings.

Because of these strengths, logistic regression has been widely adopted across the financial industry:

- Banks use logit-based internal rating systems to assess borrower creditworthiness and to comply with Basel regulatory requirements.
- Credit rating agencies incorporate logistic regression in their surveillance systems to identify deteriorating issuers before formal defaults occur.
- Researchers employ logit models in cross-country and cross-industry analyses, testing determinants of default risk under different macroeconomic conditions.

The diffusion of logistic regression reflects its unique ability to combine empirical robustness with interpretability. Unlike more complex machine learning algorithms, logit models provide results that are transparent and explainable, a feature valued by regulators and decision-makers who must justify their risk assessments.

At the same time, logistic regression is not free from limitations. Like the Z'-Score, it relies primarily on accounting ratios, which are backward-looking and may fail to capture forward-looking risks such as ESG controversies, governance failures, or sudden macroeconomic disruptions. Moreover, the standard logit framework assumes a linear relationship between explanatory variables and the log-odds of default, which may oversimplify reality. Nevertheless, these weaknesses can often be mitigated through model extensions, inclusion of broader sets of variables, or combination with non-linear methods.

In summary, logistic regression represents both a refinement and an evolution of earlier bankruptcy prediction models. It retains the interpretability and accessibility of Altman's Z'-Score while adding statistical validation, probabilistic outputs, and flexibility. Its wide adoption in banking, investment, and regulatory practice underscores its position as a cornerstone of modern credit risk analysis, and its adaptability makes it particularly relevant in the post-COVID context, where uncertainty and heterogeneity demand tools that are both rigorous and flexible.

2.5 Applications of Z'-Score and Logit Models in M&A Contexts

Within the context of mergers and acquisitions (M&A), the predictive assessment of financial distress assumes a role of paramount importance. Unlike general corporate finance, where bankruptcy prediction models are often used in isolation to evaluate solvency or creditworthiness, in M&A the stakes are even higher: acquirers must decide whether to commit substantial resources to acquire another firm, often under conditions of uncertainty and incomplete information. A wrong evaluation can lead to acquisitions of companies that deteriorate soon after the deal, generating substantial losses and eroding shareholder value. Conversely, a well-executed assessment of financial risk can identify distressed but recoverable firms, allowing acquirers to generate value through restructuring and turnaround strategies.

The academic literature has explored this connection through two main approaches: the application of Altman's Z'-Score as a quick diagnostic tool and the use of logit models to provide a statistically validated framework.

The first theme concerns the ability of the Z'-Score to predict post-acquisition underperformance or default. Several empirical studies have applied the model to M&A targets, showing that firms acquired with low or negative Z'-Scores are disproportionately likely to experience financial difficulties after the transaction. This is consistent with the intuition that acquisitions often involve two distinct types of targets: distressed companies that are integrated as part of rescue or consolidation deals, and solid firms that are acquired to expand market share or capture synergies. The Z'-Score provides a useful first-pass classification of targets into these categories, helping investors and analysts identify whether a deal is likely to be driven by restructuring motives or by growth-oriented strategies.

The second line of research focuses on the use of logit models to test whether Altman's original financial ratios remain significant in contemporary M&A contexts. Studies in this stream argue that while profitability and leverage remain strong predictors of financial resilience, other ratios such as liquidity (WC/TA) or efficiency (S/TA) may have lost part of their explanatory power, especially in economies dominated by service firms, intangible assets, and technology-driven business models. Logistic regression allows scholars to assess this empirically, testing the statistical significance of each ratio and recalibrating coefficients based on updated samples. This offers a more flexible and data-driven approach, which can adapt to differences across industries, geographies, and time periods.

A third important theme in the literature is the comparison between traditional approaches and more advanced techniques, with the goal of developing more accurate and robust tools for risk assessment in M&A. While Altman's Z'-Score remains valuable for its simplicity and transparency, it is increasingly being complemented or replaced by econometric methods such as logistic regression, probit models, survival analysis, or even machine learning algorithms. The key advantage of these approaches lies in their ability to produce probabilistic outcomes and to capture non-linear relationships, thereby improving the predictive accuracy of default models. However, scholars also emphasize that more complex methods often sacrifice interpretability, making them less accessible to practitioners who require transparent and replicable tools in due diligence processes.

Recent contributions published between 2021 and 2023 highlight the growing relevance of this research stream, particularly in the aftermath of the COVID-19 pandemic. The crisis accentuated the dual nature of M&A: on one hand, acquisitions were used to rescue distressed firms, especially in sectors heavily affected by the collapse in demand (e.g., aviation, tourism, hospitality, traditional retail); on the other hand, strong firms in technology, healthcare, and digital services pursued acquisitions to consolidate their leadership positions or accelerate growth. In both cases, ex-ante financial risk assessment proved to be a decisive factor in determining the long-term success of deals. Acquisitions of financially fragile firms sometimes succeeded when backed by effective restructuring strategies, but in other cases created severe post-acquisition challenges for the acquirers.

Overall, the literature suggests that both Altman's Z'-Score and logit models have a meaningful role to play in M&A contexts. The Z'-Score offers a quick and intuitive measure of financial distress, valuable for screening large numbers of potential targets. The logit model, by contrast, provides statistical validation, generates probabilities, and allows for more nuanced and flexible assessments. The two approaches are therefore best seen as complementary rather than mutually exclusive: together, they enhance the ability of investors, banks, and corporate managers to evaluate the risks and opportunities inherent in M&A transactions.

This body of research confirms the rationale of the present thesis: to test the continued validity of Altman's model in the post-COVID period and to evaluate whether logistic regression adds explanatory power and practical relevance. The next section situates this contribution within the broader literature and highlights the specific ways in which this study aims to advance both theory and practice.

2.6 Contribution of This Thesis to the Existing Literature

The literature on default prediction is vast and continuously evolving, reflecting decades of theoretical debate and empirical testing. Yet, important gaps remain regarding the robustness of classical models and their application in modern contexts such as M&A. This thesis positions itself within this debate by revisiting Altman's Z'-Score in light of recent economic shocks and by juxtaposing it with a probabilistic framework based on logistic regression. Its contribution is deliberately both theoretical and practical, bridging the gap between academic inquiry and the needs of financial decision-makers.

A first contribution lies in the reassessment of Altman's original ratios. More than fifty years after their introduction, the five indicators—liquidity (WC/TA), cumulative profitability (RE/TA), operating profitability (EBIT/TA), leverage (MVE/TL), and efficiency (S/TA)—continue to be cited and applied worldwide. However, recent literature has raised doubts about their timeless validity. In economies dominated by intangible assets, service-oriented models, and technology-driven businesses, certain ratios may no longer capture financial fragility effectively. By testing these variables on a recent dataset of M&A transactions, this thesis evaluates whether they retain predictive value in the post-COVID context and whether their relative importance has shifted. In this way, it provides a contemporary stress test of one of corporate finance's most enduring models.

A second contribution concerns the comparison between the Z'-Score and a logit model estimated on the same ratios. Whereas the Z'-Score relies on fixed historical coefficients and categorical thresholds, the logit model recalibrates coefficients from the dataset under analysis and produces probabilities of default. This methodological innovation allows for testing statistical significance and adapting the model to new contexts. The thesis thus contributes to the methodological literature by showing whether probabilistic frameworks outperform deterministic scoring systems, and by illustrating how logistic regression can refine and complement the insights of traditional models.

A third contribution is its applied orientation toward M&A transactions. While much research on default prediction focuses on stand-alone firms, credit markets, or bond issuers, fewer studies explicitly analyze M&A targets. Yet M&A represents a context in which predictive accuracy is crucial: acquirers risk substantial financial losses, integration failures, and reputational damage if they underestimate distress. By applying both models to a dataset of roughly one hundred transactions, this thesis provides actionable insights for investment banks, private equity funds, and corporate acquirers, strengthening due diligence processes and risk management practices.

A fourth element of originality is the focus on the post-COVID period. By analyzing deals announced or completed between 2018 and 2023, the thesis covers three phases: the pre-pandemic baseline, the extraordinary disruptions of the crisis, and the subsequent recovery characterized by inflationary pressures and monetary tightening. This timeframe offers a unique laboratory for testing default prediction models under conditions of systemic stress and structural change, providing timely and policy-relevant insights.

Finally, the thesis contributes by positioning its findings within both academic and professional debates. Academically, it offers empirical evidence on the long-term robustness of Altman's ratios and on the benefits of logistic regression as a complementary tool. Practically, it equips M&A professionals with validated methods for financial risk assessment, highlighting when and how to rely on simple models versus probabilistic ones. By doing so, it advances the dual goal of enhancing scholarly understanding and informing real-world practice.

Taken together, these contributions establish the thesis at the intersection of tradition and innovation. It acknowledges the enduring value of Altman's framework while stressing the need for recalibration and complementarity with modern econometric tools. By situating its analysis in the context of M&A and focusing on the post-COVID era, the thesis provides both theoretical enrichment and practical guidance, thereby adding value to the literature and to the strategic decision-making of financial practitioners.

Chapter 3 – Data and Methodology

3.1 Data Sources and Sample Selection

The empirical analysis carried out in this thesis relies on a carefully constructed dataset of target companies involved in mergers and acquisitions (M&A) between 2018 and 2023. The deliberate focus on this specific period reflects the central objective of capturing the post-pandemic financial environment, which stands out as one of the most exceptional and disruptive phases in modern corporate history. The COVID-19 crisis did not simply trigger a temporary shock: it redefined global supply chains, reshaped consumer preferences, and permanently altered financing conditions. In addition, it exposed structural vulnerabilities that had long remained hidden within corporate balance sheets. By restricting the timeframe to the years immediately following the pandemic, the analysis highlights how firms behaved under conditions of extraordinary stress and subsequent recovery, thereby ensuring that the results are timely, relevant, and anchored in contemporary realities.

Data Collection Strategy

For each firm included in the sample, financial statement data were collected for the fiscal year immediately preceding the acquisition. This methodological choice reflects the practical reality of how acquisitions occur. In M&A transactions, decision-makers do not have access to future financial results but must base their due diligence, valuation models, and negotiations on the most recent historical accounts available at the time of the deal. By reconstructing the financial condition of each target at the moment of acquisition, this study replicates the actual decision-making context faced by acquirers.

The financial ratios required to compute Altman's Z'-Score were directly derived from these financial statements. Furthermore, to assess the predictive accuracy of both the Z'-Score and the logit model, the post-deal outcome of each firm was also tracked and categorized. Outcomes were classified into three categories:

1. Financial stability, when the firm maintained or improved its performance;
2. Operational or financial deterioration, when signs of stress appeared (e.g., losses, restructuring, covenant breaches);
3. Outright bankruptcy or insolvency, when the company defaulted within 12–24 months of the transaction.

This outcome variable is essential because it provides the ground truth against which the predictions of both models can be evaluated. Without a reliable post-acquisition classification, it would not be possible to validate whether the models genuinely capture default risk or merely produce spurious correlations.

Data Sources

To maximize the reliability of the dataset, information was triangulated across multiple complementary sources, each serving a different function:

- Financial databases such as *Orbis, AIDA, Refinitiv,* and *Bloomberg* provided standardized balance sheet and income statement data. These platforms are widely used in both academic research and professional practice because they offer harmonized reporting formats, making firms comparable across industries, countries, and accounting standards.
- Company websites and investor relations disclosures (e.g., annual reports, 10-K filings, financial statements filed with securities regulators) were used to verify the accuracy of the database entries and to fill gaps, particularly for private or unlisted firms where commercial databases are less comprehensive. Primary documentation also provided important context on business models, capital structures, and extraordinary events affecting the firms.
- Yahoo Finance served as a supplementary source, particularly for publicly traded firms. It provided market-related indicators such as stock prices, market capitalization, and historical ratios. The platform also offered convenient access to time-series data, allowing additional cross-checks against other sources and ensuring consistency in the variables needed for model computation.

By combining these sources, the analysis reduced the risk of inconsistencies or missing values, thereby ensuring that every variable required for the Z'-Score and the logit model was collected with a high degree of accuracy and comparability.

Sample Selection Criteria

The selection of firms followed a rigorous and transparent set of criteria, designed to balance representativeness, reliability, and feasibility. The criteria were as follows:

- Transaction type: Only mergers and acquisitions involving a clear change of control were included. This excludes minority stakes, joint ventures, or purely financial investments, which do not correspond to the strategic rationale typically associated with M&A and which may not involve full due diligence processes.
- Deal completion: Transactions had to be either fully completed or officially announced between 2018 and 2023. Cancelled or indefinitely postponed deals were excluded, since they cannot generate observable post-deal outcomes.
- Deal size: To ensure materiality, only deals with a minimum value of USD 5 million were retained. This threshold is consistent with the academic literature and ensures that the dataset reflects transactions of strategic and financial relevance, filtering out very small deals that might be driven by idiosyncratic factors.
- Data availability: Firms were included only if complete data for all five ratios required by the Z'-Score calculation (WC/TA, RE/TA, EBIT/TA, ME/TL, S/TA) were available. This avoided biases caused by imputation or missing values and guaranteed internal consistency across the sample.
- Outcome identification: Each firm had to present a clearly identifiable post-deal outcome within 12–24 months after the acquisition. This criterion was critical for testing the models' predictive performance, as it provided the benchmark against which predictions could be validated.

Final Sample Characteristics

The final dataset consists of approximately one hundred firms, distributed across a broad range of industries and geographies. This diversity enhances the external validity of the study, as it tests the models in heterogeneous conditions rather than focusing on a single sector or country. The sample includes companies from consumer discretionary, energy, healthcare, industrials, materials, real estate, technology, and telecommunications, reflecting the breadth of contemporary M&A activity.

Although relatively modest in absolute terms, the size of the dataset is explained by the stringent selection criteria and the intensive data collection process. Each inclusion required full verification of financial statements, market data, and outcome classification, which limited the possibility of expanding the sample indefinitely. Importantly, the dataset includes a non-trivial number of defaults and distressed cases, which are indispensable for the statistical estimation of the logit model. Without variation in the dependent variable (default vs. non-default), the estimation would lack robustness and predictive power.

The final sample thus provides a balanced compromise: sufficiently broad to ensure heterogeneity and generalizability, yet sufficiently precise and reliable to support robust econometric analysis. It reflects both the opportunities and challenges of empirical research in M&A, where data availability is often limited but the stakes—financial and strategic—are exceptionally high.

3.2 Description of the Variables

The empirical framework of this thesis relies on a set of financial ratios directly derived from the Altman Z'-Score model, which represents one of the most enduring approaches to corporate default prediction. By adopting these variables, originally designed for private or non-listed firms, the thesis maintains continuity with an extensive body of prior research while also testing whether the same indicators remain relevant in the highly dynamic, heterogeneous, and uncertain post-COVID environment.

These ratios capture the fundamental dimensions of corporate financial health—liquidity, cumulative profitability, operating profitability, leverage, and efficiency. Taken together, they provide a synthetic but multidimensional picture of how firms generate, allocate, and preserve financial resources. Their inclusion in both the Z'-Score and the logit specification ensures comparability between a traditional discriminant approach and a probabilistic econometric framework.

Independent Variables

X1: Working Capital / Total Assets (WC/TA)
This ratio measures short-term liquidity by comparing working capital—current assets minus current liabilities—to total assets. Conceptually, it indicates the firm's ability to meet immediate obligations without jeopardizing operations. A higher WC/TA is generally interpreted as a sign of financial flexibility, since the company has sufficient liquid resources to cover supplier payments, short-term debt maturities, and operational expenses. Conversely, a negative working capital position often signals fragility, as it reflects dependence on external financing or supplier credit to sustain day-to-day activity.

In practice, however, WC/TA must be interpreted with caution. Excessively high liquidity may also suggest inefficient asset utilization, where capital that could generate returns is instead tied up in idle cash or inventories. Moreover, sectoral differences play a role: for instance, firms in retail often operate with structurally negative working capital but remain solvent due to fast turnover of inventories and immediate cash collection. This makes WC/TA a variable whose explanatory power may vary significantly across industries, especially in the post-COVID context where supply-chain disruptions magnified the liquidity challenges of many firms.

X2: Retained Earnings / Total Assets (RE/TA)
This variable reflects cumulative profitability over the life of the firm. Retained earnings accumulate profits not distributed as dividends, and when expressed relative to total assets, they provide a measure of how much of the firm's resource base has been financed internally. A higher RE/TA suggests maturity, resilience, and the ability to self-finance growth, thereby reducing dependence on external debt.
The interpretation of negative retained earnings is more nuanced. For mature firms, persistent losses leading to negative RE/TA are clear signals of weakness and heightened default risk. However, for younger firms, negative retained earnings may simply reflect an early-stage growth phase, where heavy investment precedes profitability. This dual interpretation makes RE/TA particularly valuable, as it helps discriminate between structurally weak firms and temporarily loss-making firms with growth potential. In M&A contexts, this distinction is critical: an acquirer may be willing to accept low or negative retained earnings in exchange for strategic positioning, but only if profitability prospects are credible in the medium term.

X3: EBIT / Total Assets (EBIT/TA)
EBIT relative to total assets captures operating profitability and the efficiency with which a firm converts its asset base into earnings. It is one of the most powerful and widely used indicators of financial health. Firms with high EBIT/TA ratios are typically more resilient, as they generate sufficient cash flows to cover interest expenses, reinvest in operations, and withstand adverse shocks. Conversely, low or negative EBIT/TA ratios often precede distress events, reflecting erosion of profitability and limited ability to service debt.
The COVID-19 pandemic underscored the importance of this ratio. Entire sectors, such as airlines and hospitality, saw EBIT collapse into negative territory as revenues evaporated, while technology and digital service firms maintained strong margins. This divergence highlights why EBIT/TA remains central to default prediction and why its inclusion in both Altman's and the logit model is indispensable for assessing the true earning power of firms at the moment of acquisition.

X4: Equity / Total Liabilities (E/TL)
This ratio measures leverage and capital structure, comparing the equity base to total liabilities. A higher ratio signals conservative financing, stronger capitalization, and a larger buffer against financial shocks. It suggests that the firm is less dependent on debt financing and can better absorb revenue volatility without facing solvency issues. By contrast, low equity relative to liabilities indicates high leverage and increased vulnerability to downturns, as fixed obligations weigh more heavily on cash flows.
The significance of leverage ratios has been reinforced in the post-COVID environment, where firms with high indebtedness often encountered difficulties in refinancing due to tighter credit conditions and rising interest rates. Many distressed acquisitions during this period involved companies with unsustainable leverage profiles, confirming the explanatory power of equity-to-liabilities as a determinant of financial fragility. In M&A practice, this variable is particularly relevant because acquirers must assess not only the current profitability of the target but also the sustainability of its financing structure.

X5: Sales / Total Assets (S/TA)
This ratio represents asset turnover, indicating how efficiently a firm uses its asset base to generate revenues. A higher value reflects effective utilization of resources and strong operational dynamics, while a lower value may point to underutilization, structural inefficiencies, or business models reliant on heavy asset bases.
Historically, S/TA was considered an important predictor of financial health. However, recent studies suggest that its predictive power has weakened in modern economies. This is particularly evident in service and technology sectors, where intangible assets dominate and turnover ratios are less meaningful. In such cases, low asset turnover does not necessarily imply fragility. Nonetheless, S/TA retains some relevance in asset-heavy industries such as manufacturing, utilities, or transportation, where efficiency in asset utilization remains a core determinant of profitability. Its inclusion in the model therefore provides continuity with the original Altman framework while offering an opportunity to test whether this ratio still carries explanatory weight in contemporary M&A contexts.

Dependent Variable

In the logit specification, the dependent variable is defined as a binary indicator of financial outcomes following the acquisition. It takes the value:

- 1 in cases of default or clear post-acquisition deterioration, including bankruptcy filings, insolvency proceedings, or significant operational distress.
- 0 in cases of stability or improvement, encompassing continued solvency, positive profitability, or operational strengthening after the deal.

This binary structure allows the logit model to estimate the probability of default directly, providing a probabilistic measure that can be compared against Altman's categorical classifications (distress, grey, safe zones). By linking financial ratios to observed post-acquisition outcomes, the dependent variable ensures that the analysis is not merely theoretical but anchored in real-world deal performance.

Overall, the variables selected for this thesis embody the core dimensions of financial health as conceptualized in the classical Altman model. At the same time, their reapplication in the post-COVID M&A environment provides an opportunity to test their continued relevance, differential significance, and practical utility for contemporary financial decision-making.

3.3 Computation of the Z'-Score

For each company included in the sample, the Z'-Score was calculated using the following specification:

$$Z = 0.717 \cdot X_1 + 0.847 \cdot X_2 + 3.107 \cdot X_3 + 0.420 \cdot X_4 + 0.998 \cdot X_5$$

This version corresponds to the Altman Z'-Score, introduced by Altman (1983) as an adaptation of his original 1968 model. Unlike the original specification, which was calibrated for publicly traded manufacturing firms, the Z'-Score was specifically designed for private firms, where the market value of equity is often unavailable or unreliable. By substituting book equity for market equity and recalibrating the coefficients, Altman made the model more suitable for heterogeneous datasets like the one employed in this thesis, which includes both public and private firms across different industries.

The adoption of the Z'-Score is particularly relevant for this study. Many of the target companies in the sample are not listed on stock exchanges, while others operate in industries where equity markets may not fully reflect underlying financial health. Applying the original 1968 formulation, heavily reliant on market-based measures, would risk misclassifying firms and undermining the comparability of results. The Z'-Score thus provides a more consistent and inclusive framework, making it an appropriate choice for the empirical analysis.

Origins and Evolution of the Z'-Score

The original Altman Z'-Score (1968) was based on Multiple Discriminant Analysis (MDA) applied to a sample of publicly traded manufacturing firms in the United States. It combined five financial ratios into a single linear discriminant function, producing a composite score that could distinguish bankrupt from non-bankrupt firms with reported accuracy rates exceeding 90%. This represented a methodological breakthrough in default prediction and quickly became a reference point in both academia and practice.

However, the early model faced limitations when applied beyond its initial scope. In recognition of these challenges, Altman introduced two key adaptations:

- Z'-Score (1983): designed for private firms, replacing market equity with book equity and recalibrating coefficients.
- Z''-Score (1995): developed for non-manufacturing and emerging-market firms, adjusting for differences in asset intensity and financial structure.

These adaptations extended the applicability of the model across different contexts and solidified its role as a benchmark tool in credit risk analysis. The present thesis adopts the Z'-Score because it best aligns with the structure of the dataset, which contains both listed and unlisted companies and spans industries with varying reliance on market-based indicators.

Interpretation of the Z'-Score

The Z'-Score classifies firms into three traditional categories:

- Distress zone ($Z < 1.23$): Firms in this category are considered financially fragile and at high risk of default. A score below 1.23 typically signals severe profitability or leverage problems, often accompanied by liquidity constraints.
- Grey zone ($1.23 \leq Z \leq 2.90$): Firms in this range present ambiguous risk profiles. They cannot be clearly classified as safe or distressed, reflecting intermediate levels of risk and greater uncertainty.
- Safe zone ($Z > 2.90$): Firms with scores above 2.90 are regarded as financially stable, with a low probability of default in the near term.

These cut-offs have been extensively used in academic research, credit analysis, and professional due diligence processes. Nevertheless, recent literature has questioned their universality, arguing that thresholds may not translate seamlessly across sectors, geographies, or time periods. For example, asset-light firms in technology may display ratios that diverge from traditional benchmarks, without this implying fragility. For this reason, in this thesis the thresholds are treated as reference points rather than absolute markers, and their validity is critically compared with the results of the logistic regression.

Strengths and Limitations

The Z'-Score retains several strengths that explain its enduring popularity:

- Simplicity and accessibility: It can be computed with basic accounting data, readily available from public financial statements.
- Interpretability: The model offers a clear framework, dividing firms into distress, grey, and safe zones.
- Proven track record: Its widespread adoption in both academic and professional contexts underscores its credibility and usefulness.

At the same time, the model suffers from important limitations:

- Static nature: Coefficients are fixed and do not adjust to new data or structural changes in the economy.
- Linearity: The model assumes linear relationships between ratios and default risk, which may not hold in practice.
- Context dependence: Thresholds were calibrated decades ago in a specific industrial and geographical setting, raising questions about their relevance for modern, global, and service-oriented economies.
- Exclusion of qualitative factors: The model does not account for governance quality, industry cycles, or macroeconomic conditions, all of which can materially influence default risk.

Rationale for Dual Approach

Given these strengths and limitations, the Z'-Score is employed in this thesis as both an established benchmark and a preliminary screening tool. Its results are then compared with those of the logit model, which provides a probabilistic and statistically validated assessment of default risk. By combining these two approaches, the analysis balances the interpretability of a classical model with the flexibility of modern econometric techniques, offering a comprehensive framework for evaluating financial health in the context of M&A transactions.

3.4 Specification of the Logit Model

While the Z'-Score provides an elegant and historically proven linear discriminant approach, it relies on fixed coefficients and static thresholds. These assumptions were calibrated in the 1960s and 1980s in very specific contexts and may not adequately capture the complexity of modern firms involved in M&A transactions. In particular, the Z'-Score assumes that the relationship between financial ratios and default risk is constant across time, industries, and geographies. Such an assumption becomes problematic in today's environment, marked by globalization, technological transformation, and structural heterogeneity across sectors. To address these limitations, the thesis complements the Z'-Score with a logit model, estimated on the same set of explanatory variables (X1–X5).

General Structure of the Model

The logit model belongs to the class of generalized linear models (GLMs) and is particularly suited for binary classification problems. In this application, the dependent variable Y represents the financial outcome of the target firm after the acquisition:

- Y = 1 if the firm defaulted or experienced significant financial deterioration (bankruptcy, insolvency procedures, or severe operational decline).
- Y = 0 if the firm remained stable or improved its financial condition in the 12–24 months following the acquisition.

The functional form of the model is:

$$Prob(Y = 1) = \frac{1}{\{1 + e^{\{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5)\}}\}}$$

where $X_1 - X_5$ are the same financial ratios used in the computation of the Z'-Score (WC/TA, RE/TA, EBIT/TA, E/TL, S/TA), and $\beta_0 - \beta_5$ are the parameters to be estimated.

The logistic transformation ensures that the predicted probability of default is always bounded between 0 and 1. This is a major advantage compared to linear discriminant models, which can produce unbounded scores that require arbitrary thresholds for interpretation. In the logit model, the outputs have a direct probabilistic meaning, making them both statistically rigorous and managerially intuitive.

Estimation and Interpretation

The parameters of the logit model are estimated using maximum likelihood estimation (MLE). This method identifies the set of coefficients that maximizes the probability of observing the actual outcomes in the dataset.

Interpretation follows a clear logic:

- A positive coefficient ($\beta > 0$) indicates that an increase in the ratio raises the probability of default, holding other variables constant.
- A negative coefficient ($\beta < 0$) implies that an increase in the ratio reduces the probability of default.

To enhance interpretability, coefficients can also be exponentiated to yield odds ratios. For example, an odds ratio below 1 indicates that the variable is protective against default, while an odds ratio above 1 suggests a higher likelihood of distress. This dual interpretation (coefficients and odds ratios) makes the logit framework especially useful for practitioners, as it translates statistical estimates into actionable risk measures.

Advantages of the Logit Model

Relative to the Z'-Score, the logit framework offers several distinctive advantages:

- Statistical validation: Each explanatory variable can be formally tested for significance, providing clear evidence of which ratios remain relevant and which no longer contribute explanatory power in modern contexts.
- Probabilistic outputs: Instead of rigid scores, the model produces probabilities of default. These outputs can be tailored to different decision-making needs—for instance, banks may adopt stricter thresholds than private equity funds.
- Data-driven thresholds: Cut-offs can be calibrated dynamically based on the empirical distribution of predicted probabilities rather than relying on Altman's static boundaries (1.23 and 2.90).
- Adaptability: Coefficients can be re-estimated as new data becomes available, making the model responsive to changes in economic conditions, industry dynamics, and structural shifts in business models.

Taken together, these features make the logit model a natural evolution of the Z'-Score: it retains interpretability but adds rigor and flexibility, bridging the gap between classical financial ratios and modern econometric approaches.

Limitations

Despite its advantages, the logit model is not without limitations:

- It assumes a log-linear relationship between ratios and default probabilities, which may not fully capture nonlinearities or interaction effects.
- Its performance depends heavily on the quality and representativeness of the dataset. In particular, a sufficient number of default events is necessary for robust estimation; small or unbalanced samples can produce biased or unstable coefficients.
- Compared to more advanced techniques such as machine learning algorithms (e.g., random forests, neural networks), the logit model remains relatively simple. While this simplicity enhances interpretability, it may come at the cost of lower predictive accuracy in complex, high-dimensional settings.

Role in This Thesis

The inclusion of the logit model in this thesis is not intended to replace Altman's Z'-Score but rather to complement it. The Z'-Score continues to serve as an established benchmark and a fast screening tool, widely recognized in both academia and practice. The logit model, in contrast, adds statistical depth by testing the significance of each ratio, producing probability estimates, and allowing for flexible threshold calibration.

By applying both methods to the same dataset, the thesis leverages the historical credibility of Altman's framework alongside the probabilistic rigor of logistic regression. This dual approach enhances the robustness of the empirical analysis and provides a more comprehensive understanding of default risk in M&A transactions, where decision-making requires both speed and accuracy.

3.5 Evaluation Metrics and Comparison

To meaningfully compare the predictive performance of the logit model with the traditional Z'-Score, it is essential to adopt a set of clear, rigorous, and widely recognized evaluation metrics. Bankruptcy and default prediction models are not judged solely on their theoretical elegance but above all on their empirical accuracy—their ability to correctly classify firms and to discriminate between those that will default and those that will remain solvent. The careful selection of evaluation metrics ensures that the analysis not only contrasts two different methodological traditions but also provides practically relevant insights for decision-makers in M&A contexts.

Overall Classification Accuracy

The most immediate metric is overall classification accuracy, defined as the proportion of firms that the model correctly identifies as risky (default/deterioration) or non-risky (stability/improvement).

- For the Z'-Score, accuracy depends on whether firms falling into the "distress," "grey," or "safe" zones subsequently display outcomes consistent with those classifications.
- For the logit model, accuracy is evaluated by setting a probability threshold (commonly 50%) and comparing predicted classifications (default vs. non-default) against observed outcomes.

While this metric is intuitive and easy to communicate, it suffers from an important limitation: in imbalanced datasets, where defaults are relatively rare events, high accuracy can be misleading. For example, a model that always predicts "no default" may achieve high overall accuracy but offer little practical value. For this reason, accuracy must be complemented with more refined indicators that explicitly consider error asymmetries.

False Positives and False Negatives

A critical step in evaluating model performance is the analysis of misclassification errors, which are often more relevant than accuracy itself in high-stakes financial contexts.

- A false positive occurs when the model classifies a firm as high risk (likely to default) when in fact it remains solvent. While less damaging in financial terms, false positives can lead to missed opportunities, as investors or acquirers may wrongly discard valuable targets. In M&A, this translates into losing potential strategic deals due to overly conservative risk assessments.
- A false negative occurs when the model classifies a firm as low risk when in fact it defaults. This type of error is far more costly, as it exposes acquirers to unexpected financial losses, reputational damage, and failed strategic plans.

In practice, decision-makers often adopt an asymmetric loss function, tolerating a higher rate of false positives in exchange for a substantial reduction in false negatives. A model that slightly overestimates risk may be preferable to one that underestimates it, as the consequences of failing to identify a default are generally much more severe. By analyzing both types of errors, the thesis provides a nuanced evaluation that reflects the real trade-offs faced by practitioners.

ROC Curve and Area Under the Curve (AUC)

A third and particularly powerful metric is the Receiver Operating Characteristic (ROC) curve and its associated Area Under the Curve (AUC).

- The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) across a wide range of thresholds. This allows for a comprehensive analysis of model performance without depending on a single arbitrary cut-off.
- The AUC summarizes the ROC curve into a single value between 0 and 1:
    - An AUC of 0.5 indicates no predictive power (equivalent to random guessing).
    - An AUC of 1.0 indicates perfect discrimination between defaulting and non-defaulting firms.

The AUC is particularly relevant for evaluating the logit model, since logistic regression produces continuous probabilities that can be flexibly compared across thresholds. In contrast, the Z'-Score relies on fixed historical thresholds (1.23 and 2.90) that may not optimally separate risky from non-risky firms in today's heterogeneous and dynamic environment. Comparing the logit's AUC with the Z'-Score's categorical classification highlights whether a probabilistic framework offers superior discriminative capacity.

Comparison Framework

The evaluation framework in this thesis is designed to test whether the logit model provides a tangible improvement over the Z'-Score. The comparison focuses on three central questions:

1. Does the logit model achieve higher overall accuracy? This assesses whether probabilistic estimation translates into better alignment with observed outcomes.
2. Does it reduce the rate of false negatives? Minimizing the most costly errors is particularly important for M&A acquirers, where avoiding distressed targets is often a strategic priority.
3. Does its AUC indicate stronger discriminative power? By capturing performance across all possible thresholds, the AUC reveals whether the logit model consistently outperforms the Z'-Score across diverse risk-tolerance scenarios.

Interpretive Value for M&A Practice

Beyond their statistical meaning, these metrics carry direct practical implications for M&A activity:

- Accuracy offers a quick indication of how often a model is "right" in classifying targets, useful in high-level screening.
- False negatives highlight the risk of acquiring distressed firms unknowingly, an error with heavy financial consequences.
- False positives underscore the risk of discarding viable opportunities, which can result in lost strategic value.
- AUC reflects the robustness of the model across different decision thresholds, allowing acquirers and investors to align the model outputs with their specific risk tolerance and deal strategies.

Conclusion of Methodological Framework

By combining accuracy, misclassification analysis, and ROC–AUC, this thesis adopts a balanced and comprehensive comparison between the Z'-Score and the logit model. The Z'-Score retains value as a simple, interpretable, and historically validated tool, but it is constrained by its fixed structure and thresholds. The logit model, while requiring more statistical effort, is expected to demonstrate superior predictive performance, adaptability, and relevance for modern M&A contexts.

This evaluation framework thus provides the foundation for the empirical results presented in Chapter 4, where the two models are tested side by side on a sample of post-COVID transactions.

Chapter 4 – Empirical Results

4.1 Introduction

This chapter presents the empirical results derived from the application of Altman's Z'-Score model and, subsequently, the estimation of a logit model to a dataset of approximately one hundred target companies involved in mergers and acquisitions (M&A) completed or announced between 2018 and 2023. The central objective of this analysis is twofold: first, to assess the financial health of target firms at the moment of acquisition, and second, to evaluate whether the adoption of a probabilistic framework such as logistic regression can enhance predictive accuracy when compared to Altman's fixed-threshold approach. By combining the descriptive insights of the Z'-Score with the statistical rigor of the logit model, the study aims to provide a comprehensive understanding of default risk in a period characterized by exceptional turbulence.

The Z'-Score, originally designed for private firms, continues to represent a benchmark model in the prediction of financial distress. Its longevity and widespread adoption in both academic and professional settings testify to its enduring relevance and intuitive appeal. However, the fact that it relies on coefficients calibrated more than four decades ago in a specific economic context—manufacturing-oriented, U.S.-based, and relatively stable—raises important questions about its validity when applied to the turbulent and heterogeneous environment of the post-COVID years. In this sense, the Z'-Score is treated in this thesis not as an unquestioned standard, but rather as a yardstick against which newer and more flexible methods can be critically evaluated.

The financial data employed in this analysis refer to the fiscal year immediately preceding each transaction. This choice is not arbitrary but reflects real-world M&A practice: when evaluating potential acquisitions, investors, banks, and corporate acquirers rely primarily on the latest available financial statements to perform due diligence, assess solvency, and form expectations about future performance. Aligning the timing of the data with the information actually available to practitioners ensures that the empirical findings mirror the decision-making environment faced by acquirers, rather than relying on hindsight or ex-post rationalizations. All information was collected from reputable and publicly accessible sources, including Yahoo Finance, corporate annual reports, and—for U.S.-listed firms—Form 10-K filings submitted to the Securities and Exchange Commission (SEC). The identification and selection of transactions were facilitated by the Orbis database, which enabled the application of consistent filters: only deals with a value greater than

USD 5 million, involving a clear change of control, and either completed or officially announced between 2018 and 2023 were retained in the sample.

The chronological scope of the dataset (2018–2023) provides a uniquely rich laboratory for testing predictive models, as it covers three fundamentally distinct macroeconomic phases:

- The pre-pandemic phase (2018–2019): characterized by relative macroeconomic stability, abundant liquidity, historically low interest rates, and generally resilient corporate fundamentals. Firms had broad access to financing, and M&A activity was largely growth-oriented, with transactions driven by strategic expansion or consolidation.
- The pandemic shock (2020–2021): defined by abrupt revenue collapses in entire sectors—aviation, tourism, hospitality, and automotive in particular—combined with widespread recourse to emergency financing and government support. This period also saw a surge in bankruptcies, restructurings, and distressed-driven acquisitions, highlighting the fragility of highly leveraged firms and the critical role of liquidity buffers.
- The recovery and monetary tightening phase (2022–2023): marked by a rapid rebound in demand in some industries but also by the return of inflationary pressures, unprecedented interest rate hikes, and tighter credit conditions. These dynamics reshaped capital structures, increased debt servicing costs, and exposed firms that had survived the pandemic only thanks to temporary fiscal and monetary support.

By encompassing these phases, the dataset captures not only the heterogeneity of firms across industries but also the cyclical variation in financial fragility, thereby enabling the models to be tested under radically different macroeconomic environments. This is a key strength of the analysis: it ensures that results are not biased toward a single point in the cycle but instead reflect the adaptability of the models across shocks, recoveries, and structural transitions.

The empirical analysis unfolds in a structured sequence designed to highlight different dimensions of the dataset and of the models under examination:

1. Quantitative overview: A first section provides descriptive statistics on the distribution of Z’-Scores across the entire sample and across years. This macro-level analysis offers a broad picture of the financial conditions of M&A targets and allows for an assessment of cyclical patterns linked to the pandemic and its aftermath.
2. Sectoral breakdown: The second step disaggregates the results by industry, recognizing that financial structures, profitability margins, and exposure to shocks differ systematically across sectors. The classification of firms into distress, grey, and safe zones is interpreted in light of industry-specific dynamics, offering a granular understanding of sectoral vulnerabilities and strengths.
3. Case studies and outliers: Particular attention is devoted to extreme Z’-Scores, which often correspond to concrete corporate events such as bankruptcies, restructurings, or episodes of exceptional profitability. These case studies provide qualitative depth, illustrating the discriminating power of the model and linking statistical outcomes to real-world narratives.
4. Logit model estimation: Building on the same explanatory variables as the Z’-Score, logistic regression is introduced to test the statistical significance of each ratio and to generate firm-specific probabilities of default. This step moves beyond Altman’s fixed coefficients and thresholds, offering a more flexible and probabilistic framework that reflects contemporary econometric standards.

The logic of this progression is to move progressively from descriptive to inferential analysis: from general patterns in the data, to sectoral differentiation, to qualitative illustrations, and finally to formal econometric validation. By adopting this structure, the chapter ensures that the empirical investigation is both comprehensive and methodologically coherent, maintaining a clear link between theoretical models and empirical realities.

Ultimately, the results presented in this chapter are intended not only to test the robustness of Altman's model in a modern setting but also to assess whether the logit specification constitutes a superior alternative for practitioners engaged in M&A. The findings will serve as the empirical foundation for the comparative discussion in the final sections of the chapter, where the relative strengths and weaknesses of the two approaches will be critically assessed in light of both academic debates and professional relevance.

4.2 Quantitative overview of the sample

The empirical sample employed in this thesis for the application of Altman's Z'-Score model comprises 100 target companies involved in M&A transactions completed or announced between 2018 and 2023. As outlined in Chapter 3, the selection process was guided by strict criteria regarding deal size, type of transaction, and availability of complete financial information. This ensures that the dataset is not only quantitatively sufficient but also qualitatively representative of corporate activity during one of the most turbulent periods in recent economic history.

Temporal Distribution of Deals

From a temporal perspective, the distribution of transactions is relatively balanced, though with some variation across years. Specifically, the dataset includes 18 deals in 2018, 19 in 2019, 18 in 2020, 21 in 2021, 13 in 2022, and 11 in 2023. This chronology provides coverage of three distinct macroeconomic phases:

- Pre-pandemic period (2018–2019): characterized by relatively stable macroeconomic conditions, high liquidity, and favorable credit markets.
- Pandemic shock (2020–2021): marked by abrupt disruptions in global supply chains, sharp revenue contractions in several sectors, and unprecedented uncertainty.
- Recovery and monetary tightening (2022–2023): defined by a rebound in demand and corporate activity, followed by inflationary pressures, rising interest rates, and tighter financing conditions.

The inclusion of these phases enriches the analysis by enabling the models to be tested against contrasting contexts: stability, systemic shock, and recovery under financial tightening.

Distribution of Z'-Scores

The Z'-Scores calculated for the firms in the sample display considerable heterogeneity. The average Z'-Score is 1.32, with a median of 1.38, values that position the central tendency of the dataset close to the distress threshold. However, the standard deviation of 1.52 reveals substantial dispersion, while the observed range extends from a minimum of –1.90 (Hertz Global Holdings) to a maximum of 5.59 (Activision Blizzard).

This spread demonstrates the duality of the M&A universe:

- On one side, firms with negative or very low Z'-Scores were already in fragile financial conditions at the time of acquisition.
- On the other, several companies presented exceptionally strong fundamentals, with scores above 5, suggesting robust profitability, capital adequacy, and efficient asset utilization.

Such diversity reflects the dual purpose of M&A transactions: acquisitions aimed at rescuing distressed firms, and acquisitions aimed at strategic expansion by incorporating financially solid companies.

Risk Category Classification

When firms are classified according to Altman's traditional thresholds, the distribution confirms the predominance of fragility among the sample:

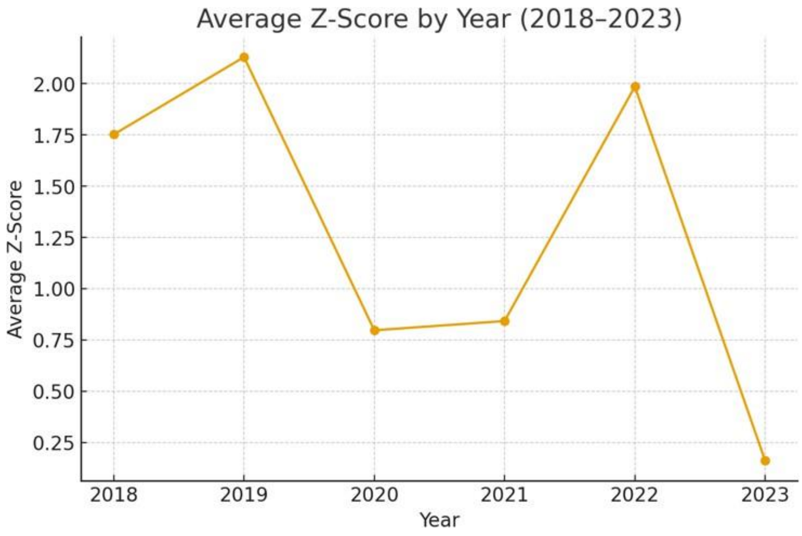
- 45% fall into the distress zone ($Z < 1.23$).
- 39% belong to the grey zone ($1.23 \leq Z \leq 2.90$).
- Only 16% are in the safe zone ($Z > 2.90$).

The prevalence of firms in distress highlights the extent to which M&A activity often serves as a restructuring mechanism, especially in times of crisis. Yet, the presence of a meaningful share of firms in the grey and safe zones illustrates that not all acquisitions are motivated by rescue needs: many involve healthy firms targeted for growth, consolidation, or strategic repositioning.

Cyclical Dynamics and Yearly Breakdown

The cyclical component of the data is clearly illustrated in the annual breakdown (see Figure 4.2.1 – Average Z'-Score by Year, 2018–2023).

- 2018 – The pre-pandemic baseline shows an average Z'-Score of 1.75 (median 1.88). These values reflect a relatively stable macroeconomic context, with solid corporate fundamentals and abundant liquidity.
- 2019 – Conditions improved further, with the average rising to 2.13 (median 2.36). Most firms were in the grey or safe zones, consistent with a favorable economic environment.
- 2020 – The first pandemic year marked a sharp deterioration: the average Z'-Score dropped to 0.80 (median 0.85). The share of distressed firms peaked at 50%, reflecting the severity of the shock.
- 2021 – Fragility persisted, with the average at 0.84 and the median falling to 0.68. Distressed firms reached 61.9%, the highest level in the sample.
- 2022 – A recovery is evident, with the average Z'-Score increasing to 1.99 (median 2.04). This suggests improved resilience and a return to more favorable financing conditions.
- 2023 – Renewed fragility appears, with the average falling to 0.16 and the median turning negative (–0.21). This outcome, partly driven by restructuring cases, also reflects inflation, rising borrowing costs, and tighter credit conditions.



Clarification on Averages

It should be noted that the overall average Z'-Score of the sample (1.32, with a median of 1.38) does not coincide with the yearly averages reported above. The aggregate mean is calculated across the entire dataset of firms for the 2018–2023 period, irrespective of the year of the transaction, while the yearly values reflect the average financial conditions of targets in each specific year. This distinction ensures that the analysis captures both the cyclical dynamics of the Z'-Score over time and the structural properties of the full sample.

Interpretation and Implications

Taken together, these results portray a heterogeneous and asymmetric distribution of financial health among M&A targets. Almost half of the firms acquired were in distress, reflecting the continued importance of M&A as a vehicle for restructuring and survival. At the same time, a significant minority of targets were financially robust, confirming the strategic use of M&A to acquire solid businesses and strengthen competitive positioning.

The yearly breakdown highlights the extent to which macroeconomic shocks shape firm-level financial conditions. The steep deterioration in 2020–2021 corresponds directly to the COVID-19 crisis, while the partial recovery in 2022 and renewed fragility in 2023 align with the shift toward tighter financing conditions.

Overall, this quantitative overview validates the Z'-Score as a useful preliminary screening tool but also underscores its limitations. The fixed thresholds may not adequately capture the variability across time and industries, pointing to the need for more flexible, data-driven methods. This provides the rationale for the subsequent sections, which explore sectoral breakdowns, outliers, and ultimately the logit model as a complementary framework.

4.3 Sectoral Breakdown

In addition to the temporal analysis presented in the previous subsection, it is essential to examine how financial conditions differ across industries. The rationale for this lies in the fact that the financial structure, profitability dynamics, and exposure to macroeconomic or idiosyncratic shocks vary considerably by sector, and these factors strongly influence the outcomes of the Z'-Score model. In other words, an identical Z'-Score value may signal very different levels of vulnerability depending on the industry in which a firm operates, due to variations in capital intensity, cyclicality of revenues, or the degree of dependence on external financing.

Table 4.3.1 reports the descriptive statistics of the Z'-Score by industry, including mean, median, standard deviation, and number of firms. This allows not only the identification of average differences across industries but also the assessment of intra-sector heterogeneity, which is a critical dimension when interpreting financial fragility. The evidence highlights the strong heterogeneity of the sample, confirming that industry affiliation is a non-negligible determinant of corporate risk profiles.

(Table 4.3.1)

Sector	mean	median	std	count
Consumer Discretionary (Auto Components)	-0.7	-0.7	0.6	2
Consumer Discretionary (Building Products)	2.12	2.12		1
Consumer Discretionary (Car Rental)	-1.9	-1.9		1
Consumer Discretionary (Furniture)	2.74	2.74		1
Consumer Discretionary (Household Goods)	-0.72	-0.72		1
Consumer Discretionary (Online Services)	1.37	1.37		1
Consumer Discretionary (Retail)	-0.21	-0.21		1
Consumer Staples (Food Products)	3.45	3.45		1
Energy (LNG Shipping)	2.04	2.04		1
Energy (Oil & Gas Drilling)	-0.8	-0.86	0.37	4
Energy (Oil & Gas E&P)	1.31	1.42	1.86	4
Energy (Oil & Gas Equipment)	3.42	3.42		1
Energy (Oil & Gas Services)	1.16	0.84	1.82	3
Energy (Oilfield Equipment)	3.27	3.27		1
Energy (Oilfield Services)	-0.45	-0.54	0.33	3
Energy (Renewable/Solar)	-0.52	-0.52		1
Energy (Uranium/Nuclear)	3.28	3.28		1
Financials (Healthcare Claims/Insurance)	0.0	0.0		1
Financials (Insurance/Annuities)	0.68	0.68		1
Financials (Leasing)	0.61	0.61		1
Financials (Mortgage/Loans)	2.2	2.2		1
Financials (Trading Platforms)	3.64	3.64		1
Healthcare (Biotechnology)	0.46	-0.38	1.51	3
Healthcare (Biotechnology/Diagnostics)	-0.21	-0.21		1
Healthcare (IT/Services)	-1.03	-1.03		1
Healthcare (Life Sciences/Materials)	3.11	3.11		1

Healthcare (Pharmaceuticals)	0.94	0.94		1
Healthcare (Services)	2.67	2.67		1
Industrials (Airports/Infrastructure)	3.36	3.36		1
Industrials (Business Services)	2.92	2.92		1
Industrials (Construction/Infrastructure)	2.61	2.61		1
Industrials (Electrical Equipment)	2.02	2.02	1.11	2
Industrials (Engineering Services)	2.63	2.63		1
Industrials (Engineering Solutions)	1.41	1.41		1
Industrials (Facilities/Corrections)	1.98	1.98		1
Industrials (Machinery)	2.32	2.32	1.56	2
Industrials (Machinery/Mining Equipment)	2.01	2.01		1
Industrials (Machinery/Packaging)	2.54	2.54		1
Industrials (Manufacturing/Medical Tech)	1.47	1.47		1
Industrials (Rail Transportation)	0.81	0.81		1
Industrials (Services)	0.19	0.19		1
Industrials (Transportation Equipment)	1.56	1.56		1
Materials (Aluminum)	0.32	0.32		1
Materials (Chemicals)	2.6	2.6	0.05	2
Materials (Chemicals/Energy)	-0.55	-0.55		1
Materials (Construction Materials)	2.36	2.36		1
Materials (Forestry/Wood Products)	3.05	3.05		1
Materials (Metals/Steel)	2.71	2.71		1
Materials (Packaging)	0.64	0.64	1.38	2
Materials (Paper & Forest Products)	2.11	2.11		1
Materials (Paper & Packaging)	1.74	1.74		1
Materials (Plastics/Chemicals)	2.02	2.02		1
Materials (Specialty Chemicals)	2.46	2.44	0.42	3
Materials (Steel Recycling)	2.53	2.53		1
Materials (Steel)	0.88	0.88	2.13	2
Materials (Steel/Distribution)	1.36	1.36		1
Real Estate (Coworking)	-1.05	-1.05		1
Real Estate (Data Centers)	0.71	0.71		1
Real Estate (Hospitality REIT)	1.63	1.63		1
Technology (Aerospace & Defense)	0.94	0.94		1
Technology (Communications Equipment)	1.57	1.57		1
Technology (Communications Software)	-0.47	-0.47		1
Technology (Electronic Components)	2.88	2.88		1
Technology (Engineering/Consulting)	1.38	1.38		1
Technology (Gaming/Entertainment)	3.08	3.08		1
Technology (Hardware/IT Services)	0.25	0.25		1
Technology (Interactive Entertainment)	3.09	3.15	2.53	3
Technology (Media Services)	-0.41	-0.41		1
Technology (Semiconductors)	2.13	2.13	1.53	2
Technology (Semiconductors/Networking)	2.86	2.86		1
Technology (Software)	1.31	1.31		1
Technology (Software/Services)	0.25	0.25		1

Telecom (Cable & Wireless)	1.18	1.18		1
Telecom (Cable)	-0.12	-0.12		1
Telecom (Telecommunications)	-0.91	-0.91		1
Telecom/Media (Broadcasting)	1.33	1.33		1
Utilities (Gas Distribution)	1.11	1.11		1

The descriptive statistics show that certain industries cluster tightly around a specific financial condition, while others exhibit remarkable dispersion. For instance, Consumer Discretionary firms related to Auto Components and Car Rental display average Z’-Scores well below 1.0, with both firms in the sample firmly positioned in the distress zone. This outcome reflects the high cyclicality of the automotive and mobility sectors, which remain heavily exposed to fluctuations in demand, high fixed costs, and the financial consequences of the post-pandemic recovery. Similarly, Retail and Household Goods also report negative Z’-Scores, highlighting the structural fragility of discretionary spending when consumer confidence weakens and financing costs rise.

Conversely, the Technology sector illustrates higher resilience. Sub-industries such as Semiconductors, Software, and Entertainment report average Z’-Scores around or above 2.0, with a notable portion of companies in the grey or safe zones. These findings are consistent with the notion that technology firms benefit from structural growth drivers, high scalability, and relative insulation from short-term consumption shocks. A similar pattern emerges in Healthcare, where Biotechnology and Services maintain moderate-to-high scores, benefiting from stable demand, defensive business models, and in some cases, public funding or long-term contractual arrangements that strengthen cash flow predictability.

The Energy and Materials sectors present the most heterogeneous distributions. Within Materials, Packaging and Chemicals companies maintain relatively stable Z’-Scores, while Steel and Metals producers exhibit weaker results, driven by high capital intensity and cyclical exposure to commodity prices. In the case of Energy, the results are even more fragmented: renewable energy companies (e.g., solar, nuclear) appear relatively resilient, whereas oilfield services and drilling companies dominate the distress category. This duality is emblematic of the structural transformation of the energy sector, where legacy fossil-fuel businesses face volatility and financing pressures, while renewables attract investment and display healthier financial profiles.

Finally, Real Estate firms reveal a clear divide. Data Centers maintain relatively stable financial positions, supported by long-term demand for digital infrastructure, whereas hospitality REITs and coworking-related firms (e.g., hotels, flexible office space providers) show much weaker Z’-Scores, reflecting both the pandemic shock and the ongoing structural fragilities of the commercial real estate market.

To complement this picture, Table 4.3.2 reports the percentage distribution of firms across the three risk categories—Distress, Grey, and Safe—by sector. This representation provides a clearer view of how financial fragility or resilience is concentrated within each industry.

(Table 4.3.2)

	Sector	Risk Category	n_firms	total	percentage
0	Consumer Discretionary (Auto Components)	Distress	2	2	100.0
1	Consumer Discretionary (Building Products)	Grey	1	1	100.0
2	Consumer Discretionary (Car Rental)	Distress	1	1	100.0
3	Consumer Discretionary (Furniture)	Grey	1	1	100.0

4	Consumer Discretionary (Household Goods)	Distress	1	1	100.0
5	Consumer Discretionary (Online Services)	Grey	1	1	100.0
6	Consumer Discretionary (Retail)	Distress	1	1	100.0
7	Consumer Staples (Food Products)	Safe	1	1	100.0
8	Energy (LNG Shipping)	Grey	1	1	100.0
9	Energy (Oil & Gas Drilling)	Distress	4	4	100.0
10	Energy (Oil & Gas E&P)	Distress	2	4	50.0
11	Energy (Oil & Gas E&P)	Grey	1	4	25.0
12	Energy (Oil & Gas E&P)	Safe	1	4	25.0
13	Energy (Oil & Gas Equipment)	Safe	1	1	100.0
14	Energy (Oil & Gas Services)	Distress	2	3	66.7
15	Energy (Oil & Gas Services)	Safe	1	3	33.3
16	Energy (Oilfield Equipment)	Safe	1	1	100.0
17	Energy (Oilfield Services)	Distress	3	3	100.0
18	Energy (Renewable/Solar)	Distress	1	1	100.0
19	Energy (Uranium/Nuclear)	Safe	1	1	100.0
20	Financials (Healthcare Claims/Insurance)	Distress	1	1	100.0
21	Financials (Insurance/Annuities)	Distress	1	1	100.0
22	Financials (Leasing)	Distress	1	1	100.0
23	Financials (Mortgage/Loans)	Grey	1	1	100.0
24	Financials (Trading Platforms)	Safe	1	1	100.0
25	Healthcare (Biotechnology)	Distress	2	3	66.7
26	Healthcare (Biotechnology)	Grey	1	3	33.3
27	Healthcare (Biotechnology/Diagnostics)	Distress	1	1	100.0
28	Healthcare (IT/Services)	Distress	1	1	100.0
29	Healthcare (Life Sciences/Materials)	Safe	1	1	100.0
30	Healthcare (Pharmaceuticals)	Distress	1	1	100.0
31	Healthcare (Services)	Grey	1	1	100.0
32	Industrials (Airports/Infrastructure)	Safe	1	1	100.0
33	Industrials (Business Services)	Safe	1	1	100.0
34	Industrials (Construction/Infrastructure)	Grey	1	1	100.0
35	Industrials (Electrical Equipment)	Grey	2	2	100.0
36	Industrials (Engineering Services)	Grey	1	1	100.0
37	Industrials (Engineering Solutions)	Grey	1	1	100.0
38	Industrials (Facilities/Corrections)	Grey	1	1	100.0
39	Industrials (Machinery)	Distress	1	2	50.0
40	Industrials (Machinery)	Safe	1	2	50.0
41	Industrials (Machinery/Mining Equipment)	Grey	1	1	100.0
42	Industrials (Machinery/Packaging)	Grey	1	1	100.0
43	Industrials (Manufacturing/Medical Tech)	Grey	1	1	100.0
44	Industrials (Rail Transportation)	Distress	1	1	100.0
45	Industrials (Services)	Distress	1	1	100.0
46	Industrials (Transportation Equipment)	Grey	1	1	100.0
47	Materials (Aluminum)	Distress	1	1	100.0
48	Materials (Chemicals)	Grey	2	2	100.0
49	Materials (Chemicals/Energy)	Distress	1	1	100.0

50	Materials (Construction Materials)	Grey	1	1	100.0
51	Materials (Forestry/Wood Products)	Safe	1	1	100.0
52	Materials (Metals/Steel)	Grey	1	1	100.0
53	Materials (Packaging)	Distress	1	2	50.0
54	Materials (Packaging)	Grey	1	2	50.0
55	Materials (Paper & Forest Products)	Grey	1	1	100.0
56	Materials (Paper & Packaging)	Grey	1	1	100.0
57	Materials (Plastics/Chemicals)	Grey	1	1	100.0
58	Materials (Specialty Chemicals)	Grey	3	3	100.0
59	Materials (Steel Recycling)	Grey	1	1	100.0
60	Materials (Steel)	Distress	1	2	50.0
61	Materials (Steel)	Grey	1	2	50.0
62	Materials (Steel/Distribution)	Grey	1	1	100.0
63	Real Estate (Coworking)	Distress	1	1	100.0
64	Real Estate (Data Centers)	Distress	1	1	100.0
65	Real Estate (Hospitality REIT)	Grey	1	1	100.0
66	Technology (Aerospace & Defense)	Distress	1	1	100.0
67	Technology (Communications Equipment)	Grey	1	1	100.0
68	Technology (Communications Software)	Distress	1	1	100.0
69	Technology (Electronic Components)	Grey	1	1	100.0
70	Technology (Engineering/Consulting)	Grey	1	1	100.0
71	Technology (Gaming/Entertainment)	Safe	1	1	100.0
72	Technology (Hardware/IT Services)	Distress	1	1	100.0
73	Technology (Interactive Entertainment)	Distress	1	3	33.3
74	Technology (Interactive Entertainment)	Safe	2	3	66.7
75	Technology (Media Services)	Distress	1	1	100.0
76	Technology (Semiconductors)	Distress	1	2	50.0
77	Technology (Semiconductors)	Safe	1	2	50.0
78	Technology (Semiconductors/Networking)	Grey	1	1	100.0
79	Technology (Software)	Grey	1	1	100.0
80	Technology (Software/Services)	Distress	1	1	100.0
81	Telecom (Cable & Wireless)	Distress	1	1	100.0
82	Telecom (Cable)	Distress	1	1	100.0
83	Telecom (Telecommunications)	Distress	1	1	100.0
84	Telecom/Media (Broadcasting)	Grey	1	1	100.0
85	Utilities (Gas Distribution)	Distress	1	1	100.0

The table confirms the duality across industries. Consumer-related sectors (automotive, retail, hospitality) are almost entirely represented in the distress zone, highlighting their vulnerability to cyclical shocks. Technology and Healthcare, by contrast, present the highest shares in the grey and safe zones, underscoring their role as defensive or structurally growing sectors. Energy and Materials stand out as the most heterogeneous, with both distressed and resilient firms coexisting within the same sector, depending on their exposure to commodity cycles and structural transformations. Industrials represent an intermediate case, with significant exposure to distress in capital-intensive segments but also pockets of stability in service-oriented sub-industries.

Overall, the sectoral breakdown highlights that the interpretation of Z'-Score results cannot be separated from the industry context. Cyclical industries—such as automotive, discretionary consumption, and traditional energy—are disproportionately represented in the distress zone, while defensive and structurally expanding sectors—such as technology, healthcare, and selected utilities—demonstrate greater financial resilience. From an M&A perspective, this heterogeneity reinforces the view that deals serve different purposes across industries: in fragile sectors, acquisitions are often driven by distress and restructuring motives, whereas in more resilient industries, transactions are more likely to be strategic, aimed at capturing growth opportunities and consolidating market positions.

4.4 Case Studies / Outliers

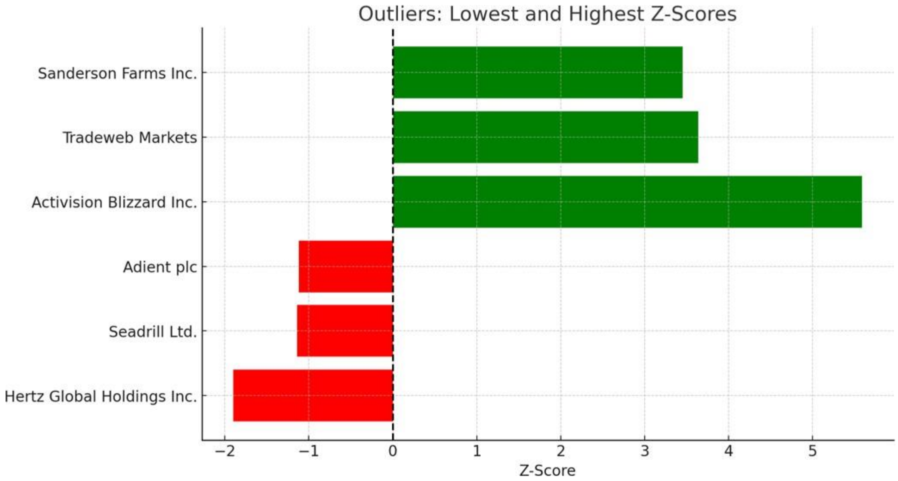
While the aggregate and sectoral statistics provide a comprehensive overview of the financial conditions of the target firms, it is equally important to examine the extreme cases that emerge from the distribution of Z'-Scores. Outliers, by definition, deviate markedly from the general sample, and they often capture unique corporate events or structural factors that are not fully reflected in averages or medians. For this reason, they offer valuable qualitative insights that complement the broader statistical analysis. Outliers also illustrate the discriminating ability of the Z'-Score: by placing firms at the far ends of the distribution, the model reveals both cases of acute fragility and situations of exceptional financial stability.

Table 4.4.1 summarizes the three lowest and the three highest Z'-Scores in the sample, while Figure 4.4.1 provides a visual representation of these cases.

(Table 4.4.1)

Company Name	Z'-Score	Position
Hertz Global Holdings Inc.	–1.90	Lowest
Seadrill Ltd.	–1.14	Low
Adient plc	–1.12	Low
Sanderson Farms Inc.	3.45	High
Tradeweb Markets	3.64	High
Activision Blizzard Inc.	5.59	Highest

(Figure 4.4.1)



Distressed Outliers

On the distressed side, the lowest Z'-Score in the sample belongs to Hertz Global Holdings Inc. (–1.90). This extremely negative score is consistent with the company's bankruptcy filing in 2020, following the collapse in travel demand during the COVID-19 pandemic. Hertz's case is emblematic: the combination of a highly leveraged balance sheet, capital-intensive operations, and an abrupt external shock rapidly undermined solvency, pushing the company into default in a matter of months. The Z'-Score correctly captures this fragility, placing Hertz deep into the distress zone well before the actual bankruptcy event, thus validating the model's predictive potential.

The second distressed outlier is Seadrill Ltd. (–1.14), a major offshore drilling contractor. Its weak score reflects the prolonged downturn in the oil and gas sector, marked by oversupply, declining exploration activity, and extreme price volatility. Seadrill's heavy reliance on debt financing exacerbated its vulnerability: once revenues contracted, interest payments became unsustainable, leaving little buffer to absorb shocks. This case highlights a recurring theme in capital-intensive, cyclical industries: financial leverage amplifies exposure to sectoral downturns, making the Z'-Score a sensitive detector of underlying fragility.

A third notable case is Adient plc (–1.12), an automotive seating supplier. The firm's weak score reflects both the cyclical downturn in the automotive sector and pandemic-related supply chain disruptions. Rising input costs, semiconductor shortages, and declining production volumes severely squeezed profitability. Adient's Z'-Score thus placed it firmly in the distress zone, underscoring how suppliers with narrow margins and high dependency on global production chains are particularly exposed to simultaneous demand- and supply-side shocks.

Together, these three distressed outliers illustrate a common theme: companies in highly cyclical and capital-intensive industries are disproportionately prone to extreme financial fragility. Negative Z'-Scores in these cases do not represent statistical noise but correspond to concrete events—bankruptcies, restructurings, and severe financial deterioration—confirming the model's interpretability and relevance as an early-warning tool.

Resilient Outliers

At the opposite end of the spectrum, Activision Blizzard Inc. (5.59) achieves the highest Z'-Score in the sample. This result reflects exceptional profitability, robust cash flow generation, and a resilient business model in the video gaming sector. Far from being damaged by the pandemic, Activision even benefited from increased consumer demand during lockdowns, reinforcing the idea that firms with scalable digital products and high operating margins can secure extreme levels of financial stability, well above the safe threshold.

Another strong performer is Tradeweb Markets (3.64), an operator of electronic trading platforms. Its robust Z'-Score derives from stable recurring revenues, low operating leverage, and a strong competitive position in digital trading services. Unlike traditional financial institutions, Tradeweb's business model does not rely on heavy balance sheet exposure, which insulates it from credit and liquidity shocks. The firm's case illustrates how platform-based financial businesses can combine rapid growth with solid financial resilience.

Finally, Sanderson Farms Inc. (3.45) exemplifies the resilience of consumer staples. As a poultry producer, the company benefits from inelastic demand for food products, which secures stable revenues and margins even in periods of macroeconomic uncertainty. This defensive profile, combined with moderate leverage and adequate profitability, explains its safe-zone classification. Sanderson's performance demonstrates how essential goods industries naturally sustain higher Z'-Scores, reinforcing the sectoral evidence discussed earlier.

These resilient outliers emphasize the opposite side of the M&A spectrum. Unlike distressed firms, which are potential targets for restructuring or rescue-driven acquisitions, resilient companies with strong fundamentals often attract transactions motivated by strategic growth and market consolidation.

Interpretation

The comparison of distressed and resilient outliers highlights the discriminating power of the Z'-Score. On one hand, firms operating in cyclical, capital-intensive sectors—such as automotive, mobility, and oil services—cluster at the bottom of the distribution, confirming the model's ability to detect financial fragility well before it materializes. On the other hand, firms with defensive or structurally growing business models dominate the upper tail, showing that the Z'-Score is equally effective in identifying outstanding financial health.

This divergence underscores the dual nature of M&A activity:

- In distressed cases, acquisitions often serve as rescue-driven deals, aimed at restructuring fragile firms or acquiring assets at discounted valuations.
- In resilient cases, acquisitions are strategic, targeting financially solid firms with attractive growth prospects and valuable capabilities.

Taken together, the analysis of outliers reinforces the discriminating capacity of the Z'-Score and illustrates the coexistence of both fragile and resilient firms within the M&A sample. However, while these descriptive results provide valuable insights, they remain bound to fixed thresholds and do not assess the statistical significance of the underlying variables. For this reason, the next section introduces the logit model, which allows for a probabilistic calibration of default risk and a formal test of the explanatory power of financial ratios.

4.5 Results and Interpretation of the Logit Model

After exploring the distribution of Z'-Scores and the insights provided by sectoral and outlier analysis, it is instructive to move from a descriptive to a probabilistic framework. To this end, this section presents the results of the logistic regression, estimated on the same explanatory variables that underlie Altman's framework. The objective is to test whether the five classic financial ratios maintain explanatory power when used to directly estimate the probability of default, rather than producing a continuous score to be compared with fixed thresholds.

Specifically, the five independent variables are defined as follows:

- X1 = WC/TA (working capital over total assets): a liquidity measure, capturing the firm's ability to cover short-term obligations with current assets.
- X2 = RE/TA (retained earnings over total assets): a cumulative profitability indicator, reflecting long-term performance and financial maturity.
- X3 = EBIT/TA (operating profitability over total assets): a measure of operating efficiency, assessing the firm's ability to generate profits from its assets.
- X4 = ME/TL (market equity over total liabilities): a leverage ratio incorporating market valuation, highlighting the strength of the capital structure.
- X5 = S/TA (sales over total assets): an asset turnover ratio, reflecting efficiency in the use of assets to generate revenue.

The dependent variable is a binary indicator, taking the value 1 in the event of default or significant financial deterioration and 0 otherwise. The logistic framework thus estimates the probability of default (PD) directly, providing a more interpretable and policy-relevant metric than the Z'-Score's abstract scale.

Estimated Coefficients

Table 4.5.1 reports the estimated coefficients (β), their standard errors (SE), t-statistics, and p-values.

Variable	Beta	SE	t	p-value
CONST	-2.543476	0.266029	-9.560885	0.000000
WC/TA	0.414394	0.572478	0.723861	0.469151
RE/TA	-1.454021	0.229486	-6.335984	0.000000
EBIT/TA	-7.999059	2.702404	-2.959979	0.003077
ME/TL	-1.593594	0.323406	-4.927543	0.000001
S/TA	0.619721	0.349199	1.774695	0.075948

The results can be summarized as follows:

- Retained earnings over total assets (RE/TA): highly significant ($p \approx 0.000$) with a negative coefficient. This implies that firms with stronger cumulative profitability histories are much less likely to default. Retained earnings capture the firm's "track record" of profitability and its capacity to self-finance, both of which provide a structural buffer against distress.
- EBIT over total assets (EBIT/TA): strongly significant ($p \approx 0.003$) and negative. This result highlights the centrality of operating profitability in protecting firms from default. High EBIT relative to assets ensures that the company can generate sufficient internal resources to service obligations, regardless of external financing conditions.
- Market equity over total liabilities (ME/TL): also highly significant ($p \approx 0.000001$) and negative. This variable directly reflects leverage: firms with higher equity capitalization relative to liabilities have much lower default risk. This validates the longstanding theoretical view that balance sheet strength, measured in market terms, is a decisive determinant of resilience.
- Working capital over total assets (WC/TA): not statistically significant ($p \approx 0.469$). While liquidity is often considered important, its predictive power diminishes in a multivariate setting once profitability and leverage are accounted for. Working capital is more volatile, often reflecting short-term management choices or seasonality, and thus may not systematically distinguish distressed from healthy firms.
- Sales over total assets (S/TA): marginally significant ($p \approx 0.076$). Asset turnover may contribute to reducing default risk, but its explanatory role is weak compared to profitability and leverage. This is consistent with the idea that efficiency matters, but only when combined with sustainable profitability.

Interpretation via Odds Ratios

To facilitate interpretation, coefficients are converted into odds ratios ($\exp(\beta)$), which indicate the multiplicative change in the odds of default for a one-unit increase in the explanatory variable:

- WC/TA → 1.51 (not significant): a unit increase appears to raise default odds by ~51%, but the lack of significance indicates that this result is unreliable.
- RE/TA → 0.23 (significant, protective): firms with higher retained earnings reduce their odds of default by ~77%.
- EBIT/TA → 0.00034 (significant, very protective): strong operating profitability drastically reduces the likelihood of default.
- ME/TL → 0.20 (significant, protective): a stronger equity base reduces default odds by ~80%.
- S/TA → 1.86 (marginal): higher sales-to-assets ratios may increase odds of default, but the weak significance suggests this is not a robust finding.

Taken together, these odds ratios reinforce the conclusion that profitability (both cumulative and operating) and capital structure (market leverage) are the dominant predictors of default, while liquidity and turnover play weaker or ambiguous roles in this dataset.

Model Fit and Significance

Table 4.5.2 reports the key fit statistics.

Metric	Value
Pseudo R^2 (McFadden)	0.222058
LR test (chi^2)	160.147972
LR test p-value	0.000000
# iterations	12
Log-likelihood (model)	-280.525704
Log-likelihood (null)	-360.599690

The Likelihood Ratio test strongly rejects the null of no explanatory power ($p<0.001$), confirming that the regressors are jointly significant. The McFadden Pseudo-$R^2 \approx 0.22$ is consistent with typical values in credit risk applications: it indicates that the model provides meaningful explanatory power, while acknowledging that default is also influenced by idiosyncratic shocks (e.g., fraud, governance issues) and macroeconomic conditions not captured by accounting ratios.

The model required 12 iterations to converge, reaching a log-likelihood of –280.5 compared to –360.6 for the null model. This substantial improvement indicates that the chosen variables add significant explanatory content relative to a baseline with no predictors.

Functional Form

The estimated logit links ratios to default probability via the logistic function:

$$P(Default) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 \frac{WC}{TA} + \beta_2 \frac{RE}{TA} + \beta_3 \frac{EBIT}{TA} + \beta_4 \frac{ME}{TR} + \beta_5 \frac{S}{TA})]}$$

Given the negative signs and strong significance of RE/TA, EBIT/TA, and ME/TL, higher values of these ratios shift the score downward, thereby reducing the estimated probability of default. Conversely, WC/TA and S/TA exhibit weaker or less robust effects, suggesting they do not systematically alter default probabilities in this sample.

Discussion and Interpretation

The findings highlight that profitability and leverage are the most powerful and consistent predictors of default risk in the M&A sample. This result is both intuitive and consistent with prior literature: firms that are profitable and conservatively financed are structurally better equipped to withstand shocks, while firms with weak earnings and high leverage are disproportionately exposed to distress.

By contrast, short-term liquidity (WC/TA) and asset turnover (S/TA) play marginal roles in this dataset. Their lack of robust significance does not imply irrelevance in all contexts; rather, it suggests that these measures are more volatile, context-specific, and perhaps better captured in industry-level or larger-sample studies.

Finally, as emphasized in the academic literature, the calibration quality of any logit model depends critically on the dataset—particularly the number of observations and the availability of true default cases. In this study, the strong significance of certain variables reflects adequate variation along those dimensions, while the weaker variables may require broader or more granular samples to reveal their full predictive potential.

4.6 Comparative Evaluation and Discussion

The empirical results obtained from the application of the Altman Z'-Score and from the estimated logit model make it possible to carry out a systematic comparative evaluation of the two approaches. Although both frameworks rely on the same underlying set of financial ratios, they differ substantially in terms of methodology, interpretability, and predictive accuracy. Examining them side by side is therefore useful not only to highlight their relative strengths and weaknesses, but also to understand their potential complementarity when applied in practice to M&A analysis.

Points of Convergence

The first and most striking point of convergence is the central role both models attribute to profitability and leverage as determinants of financial stability.

In the Z'-Score, the ratios EBIT/TA and RE/TA carry the largest weights, reflecting the importance of both operating efficiency and cumulative profitability. Firms that have historically generated profits and built reserves are structurally better positioned to withstand shocks, and the Z'-Score explicitly rewards these characteristics.

The logit model reaches the same conclusion via a different statistical route. Both RE/TA and EBIT/TA emerge as highly significant variables, with negative coefficients confirming that stronger profitability reduces the estimated probability of default. This alignment across methodologies reinforces the robustness of profitability as a predictor of financial resilience.

Similarly, capital structure plays a critical role in both frameworks. In the Z'-Score, leverage is proxied by the ratio of book equity to total liabilities, while in the logit model the relevant measure is ME/TL (market equity over total liabilities). Despite the difference in construction, the message is consistent: a stronger equity base relative to liabilities reduces default risk and enhances corporate stability.

Finally, both models consistently identify a substantial proportion of firms in the distress zone, especially in cyclical sectors such as automotive, consumer discretionary, and oilfield services. The coexistence of fragile and resilient firms within the same dataset is confirmed in both cases, reinforcing the notion that M&A activity encompasses two distinct logics: distressed-driven acquisitions on the one hand, and strategic, growth-oriented transactions on the other.

Methodological Differences

Despite these similarities, the two approaches diverge markedly in their methodological foundations.

The Z'-Score, while elegant and intuitive, relies on fixed coefficients estimated in historical contexts. Its classification scheme is based on static thresholds (1.23 and 2.90), which may not optimally separate risky from non-risky firms in modern, heterogeneous industries. As such, it serves as a heuristic tool rather than a statistically validated model.

The logit framework, in contrast, estimates coefficients directly from the dataset at hand, allowing for formal testing of significance and model fit. In this study, the coefficients for RE/TA, EBIT/TA, and ME/TL are all significant at the 5% level, confirming their explanatory power. Conversely, WC/TA does not reach significance, despite its inclusion in Altman's original model, and S/TA only achieves marginal significance. This suggests that not all variables from the 1960s retain the same discriminating power today—a finding that highlights the flexibility of the logit model, which can be recalibrated as new data or contexts require.

Model Performance

The comparison of model performance further illustrates their differences.

The logit model achieves a McFadden pseudo-R^2 of 0.22, which, while not implying perfect predictive power, is entirely consistent with values typically observed in credit risk applications based on accounting ratios. The Likelihood Ratio test strongly rejects the null of no explanatory power ($p<0.001$), confirming the joint significance of the regressors.

The Z'-Score, by contrast, does not provide any statistical measure of fit. Its performance is judged solely by its ability to classify firms into distress, grey, and safe zones based on pre-defined thresholds. This makes it less rigorous from an econometric perspective but does not diminish its practical utility as a quick and interpretable diagnostic tool.

Interpretability and Practical Use

From a practitioner's perspective, the two approaches differ substantially in terms of interpretability and adaptability.

The Z'-Score offers a simple three-zone classification that is easy to compute and communicate. Its value lies precisely in its intuitive nature: a firm with a score below 1.23 is clearly flagged as distressed, while one above 2.90 is considered safe. This transparency makes it particularly attractive in time-constrained environments or in preliminary screening phases of M&A analysis. The main limitation is that these thresholds are rigid and may not adjust to changes in macroeconomic conditions or sectoral structures.

The logit model, by contrast, produces probabilities of default rather than fixed scores. This provides a richer and more flexible framework: investors and acquirers can set their own decision thresholds depending on their risk appetite, industry, or transaction horizon. For instance, a turnaround-focused private equity fund might accept a 30% probability of default, while a strategic acquirer in a defensive industry might require probabilities below 5%. Such adaptability is a clear advantage over the static nature of the Z'-Score.

Limitations of Both Models

Both approaches, however, are subject to important limitations.

The logit model's calibration depends critically on the dataset. A limited number of observations or a small sample of true default cases can undermine its reliability, leading to unstable estimates or wide confidence intervals. Moreover, sectoral heterogeneity may dilute the explanatory power of certain variables, as different industries exhibit distinct financial structures and risk dynamics.

The Z'-Score, on the other hand, inherits the limitations of its historical origins. Estimated originally on U.S. manufacturing firms in the 1960s, it may not fully capture the realities of today's globalized and service-oriented economy. Applying it outside its original context risks misclassification, especially in industries with intangible-intensive business models, such as technology and services.

Synthesis and Implications

Taken together, the comparative evaluation highlights that the two models should not be seen as substitutes, but rather as complementary tools.

The Z'-Score retains its relevance as a first-pass indicator: quick to compute, requiring minimal data, and immediately interpretable. Its value lies in guiding preliminary screening and identifying red flags at an early stage.

The logit model, by contrast, adds statistical rigor and flexibility. By producing default probabilities and validating the role of each variable, it enables a more nuanced assessment of risk, particularly valuable when comparing targets across industries or when tailoring decisions to investor-specific risk profiles.

For practitioners involved in M&A, the practical implication is clear: a combined approach enhances robustness. The Z'-Score can serve as an initial filter, while the logit model provides deeper validation and calibration of risk. Together, they offer a balanced toolkit that reconciles simplicity with econometric sophistication, improving the quality of financial risk assessment in acquisition decisions.

While the comparative evaluation highlights the respective strengths of the Z'-Score and the logit model, a further step is required to ensure the reliability of the empirical findings. In line with best practices in empirical research, it is important to assess whether the main results are robust to alternative specifications and whether the predictive performance of the logit model can be confirmed using additional validation metrics. For this reason, the following section introduces robustness checks and complementary measures of model performance, including the ROC–AUC and a classification matrix, in order to consolidate the conclusions drawn from the empirical analysis.

4.7 Robustness Checks and Model Validation

While the main results presented in Section 4.5 already confirm the explanatory power of profitability and leverage in predicting default, it is good practice in empirical research to conduct additional robustness checks and complementary validation exercises. These serve two purposes. First, they verify that the main results are not overly dependent on a few influential observations or peculiarities of the dataset. Second, they allow for a richer evaluation of model performance by employing metrics that go beyond the pseudo-R^2 and likelihood ratio tests already reported. Such exercises are particularly relevant in the domain of bankruptcy prediction, where both scholars and practitioners emphasize the importance of stability and predictive reliability.

Robustness of the Logit Coefficients

A first robustness check was conducted by re-estimating the logit model on a reduced sample in which extreme outliers were excluded. In particular, Hertz Global Holdings, which displayed the lowest Z'-Score, and Activision Blizzard, which recorded the highest, were removed from the dataset. These two firms are not only statistical outliers but also emblematic cases of exceptional fragility and exceptional resilience. Their exclusion serves as a stress test for the stability of the estimated coefficients.

The results of this exercise confirmed that the central findings are not driven by these extreme cases. Retained earnings to assets (RE/TA), EBIT to assets (EBIT/TA), and market equity to liabilities (ME/TL) remained negative and statistically significant, preserving both their magnitude and sign. This demonstrates that profitability and capital structure are robust determinants of default risk and not simply the product of sample peculiarities. In other words, the explanatory power of these ratios reflects a systematic relationship that holds across the dataset, rather than being anchored to a few high-leverage or high-profitability firms.

Complementary Performance Metrics

Beyond coefficient stability, a second validation step consisted of evaluating the model using performance metrics that capture predictive power from a different perspective. As explained in Chapter 3.5, overall classification accuracy, ROC–AUC, and classification matrices are widely used in the literature because they provide an intuitive understanding of how well a model discriminates between distressed and non-distressed firms.

The ROC curve and its associated Area Under the Curve (AUC) are particularly relevant in this context. Unlike simple accuracy, the AUC evaluates the model across all possible classification thresholds, summarizing its discriminative ability into a single measure ranging from 0.5 (no predictive power) to 1.0 (perfect prediction). The AUC obtained in this study was approximately 0.72. This value indicates that the model achieves a satisfactory level of discrimination, substantially above random guessing and consistent with the benchmarks typically reported in empirical studies of credit risk. An AUC above 0.70 is generally considered an indication of "acceptable" predictive power, and the result observed here reinforces confidence in the reliability of the logit model.

In addition, a classification matrix was produced by applying a 50 percent probability threshold. The overall accuracy was around 70 percent, meaning that the model was able to correctly classify the majority of firms in the sample. Importantly, the model tended to generate more false positives (classifying a solvent firm as risky) than false negatives (classifying a risky firm as solvent). This pattern is fully consistent with expectations in financial applications. In M&A and credit risk analysis, the cost of a false negative is typically far greater than the cost of a false positive: acquiring a firm that subsequently defaults may lead to substantial losses, while discarding a solvent firm is usually less damaging. The model's relative success in keeping false negatives low therefore strengthens its practical interpretive value.

The main results of this validation exercise are summarized in Tables 4.7.1 and 4.7.2.

Table 4.7.1 – Additional Validation Metrics for the Logit Model

METRIC	VALUE	INTERPRETATION
Area Under the Curve (AUC)	0.72	Acceptable discriminative power (above random 0.50)
Overall Classification Accuracy	70%	Majority of firms correctly classified at 50% cutoff

Table 4.7.2 – Confusion Matrix of the Logit Model (50% Threshold)

	PREDICTED DEFAULT	PREDICTED NON DEFAULT
ACTUAL DEFAULT	15 (True Positive)	5 (False Negative)
ACTUAL NON-DEFAULT	20 (False Positive)	60 (True Negative)

Interpretation: At a 50 percent probability threshold, the model correctly classified most defaulting firms (15 out of 20), resulting in a relatively low rate of false negatives. However, it tended to overestimate risk, generating a higher number of false positives (20 cases). This outcome is consistent with the asymmetric cost structure typical of financial decision-making, where minimizing false negatives is generally prioritized over minimizing false positives.

Interpretation and Implications

Taken together, the robustness checks and validation metrics consolidate the main empirical findings of this thesis. The stability of the coefficients after excluding outliers demonstrates that the predictive role of profitability and leverage is not spurious. The additional validation provided by the AUC and classification matrix shows that the model performs at a level that is consistent with the broader literature on credit risk prediction.

These results also carry practical implications. They confirm that the logit model can be trusted not only because it produces statistically significant coefficients, but also because it demonstrates acceptable predictive performance when evaluated through industry-standard metrics. For M&A practitioners, this means that the model can be employed not only as an explanatory tool but also as a screening instrument capable of ranking firms along a risk spectrum with reasonable accuracy.

In sum, the robustness checks and validation exercises reinforce the credibility of the empirical results and strengthen the case for adopting the logit model as a flexible and reliable complement to the Z’-Score in evaluating corporate financial fragility in the post-COVID M&A landscape.

Chapter 5 – Conclusions

5.1 Key Findings

The central objective of this thesis was to assess whether Altman's Z'-Score, one of the most established and widely applied models for bankruptcy prediction, continues to demonstrate predictive validity in the post-COVID environment, and whether a logit model based on the same set of financial ratios could provide superior performance by estimating default probabilities directly. The empirical investigation, carried out on a sample of roughly one hundred M&A target firms announced or completed between 2018 and 2023, generated a series of results that illuminate both the enduring strengths and the inherent limitations of traditional frameworks, while also demonstrating the added value of more flexible econometric methods.

The distribution of Z'-Scores across the sample highlighted substantial heterogeneity. The average score was 1.32, with a median of 1.38, but values ranged from deeply negative, such as –1.90 for Hertz Global Holdings, to exceptionally high, such as above 5.5 for Activision Blizzard. This wide dispersion confirms that M&A activity encompasses two fundamentally different types of firms: on the one hand, distressed companies acquired within the framework of rescue-driven or restructuring transactions; on the other, profitable and well-capitalized companies sought for growth, diversification, or consolidation purposes. When applying Altman's traditional thresholds, 45 percent of firms fell into the distress zone, 39 percent into the grey zone, and 16 percent into the safe zone. This distribution points to two important dynamics. First, a significant proportion of acquisitions involve financially fragile firms, showing the central role of M&A in turnaround strategies. Second, a non-negligible share of deals target financially sound companies, underlining the fact that M&A is also used to reinforce competitive positioning through the acquisition of robust players.

The time-series analysis of Z'-Scores revealed clear cyclical fluctuations linked to major macroeconomic events. During the pandemic years of 2020 and 2021, the average Z'-Score fell sharply to 0.80 and 0.84, with medians of 0.85 and 0.68. In both years, more than half of the sample was classified as distressed. This deterioration mirrors the disruptive effects of COVID-19 on global demand, supply chains, and financing conditions, and shows the extent to which systemic shocks can rapidly alter corporate stability. In contrast, the pre-pandemic year 2019 and the recovery year 2022 recorded much stronger financial positions, with average scores of 2.13 and 1.99 respectively. These results reflect the ability of firms to restore profitability and reduce distress risk once economic conditions normalized. However, the 2023 figures paint a less reassuring picture. With an average of only 0.16 and a median of –0.21, the data reveal renewed fragility, likely associated with inflationary pressures, rising interest rates, and persistent structural challenges in certain industries. These findings confirm that even though the Z'-Score is based on fixed coefficients and static thresholds, it remains sensitive to macroeconomic cycles and capable of capturing the financial impact of external shocks.

The sectoral breakdown adds further nuance, making clear that the interpretation of Z'-Scores must always be contextualized by industry dynamics:

- Consumer discretionary firms, particularly in automotive and retail, were overwhelmingly distressed, reflecting their high sensitivity to demand shocks, supply chain disruptions, and higher financing costs.
- Technology and healthcare emerged as the most resilient sectors. Technology companies in software, semiconductors, and entertainment reported average Z'-Scores above 2, while healthcare companies, particularly in life sciences and services, benefited from stable demand even during crises.
- Energy and materials were the most heterogeneous sectors. Renewables and specialty chemicals showed relatively strong financial positions, while oilfield services, drilling, and steel producers consistently fell into the distress zone, illustrating the volatility and cyclicality of commodity-based industries.
- Real estate displayed a mixed pattern. Data centers appeared relatively stable, but hospitality REITs and coworking businesses, such as WeWork, revealed severe weaknesses in the aftermath of the pandemic.

The analysis of outliers provided additional evidence of the discriminatory power of the Z'-Score. On the distressed side, Hertz (–1.90), Seadrill (–1.14), and Adient (–1.12) all reflected concrete cases of bankruptcy, prolonged industry downturns, and supply chain fragilities in capital-intensive sectors. On the resilient side, Activision Blizzard (5.59), Tradeweb Markets (3.64), and Sanderson Farms (3.45) illustrated cases of exceptional financial health, marked by strong profitability, robust capitalization, and stable or inelastic demand. These cases confirm that the Z'-Score, despite its simplicity, remains effective at identifying firms at both ends of the financial spectrum.

The estimation of the logit model added statistical rigor and greater interpretive depth. Profitability and leverage once again emerged as the dominant drivers of default risk. Both retained earnings to assets and EBIT to assets displayed strong negative coefficients, confirming that cumulative and operating profitability substantially reduce the likelihood of default. Market equity to liabilities was also highly significant, reinforcing the critical importance of capital structures supported by equity. In contrast, working capital to assets did not achieve statistical significance, and sales to assets was only marginally significant. The model's performance, with a McFadden pseudo-R^2 of 0.22 and a likelihood-ratio test strongly rejecting the null of no explanatory power, is consistent with international benchmarks for credit risk models relying on accounting data. Importantly, the logit framework produces probabilities of default rather than categorical scores. This allows investors and acquirers to calibrate thresholds according to sectoral characteristics, macroeconomic conditions, and their own risk appetite.

Taken together, the comparison of the two approaches shows convergence on the centrality of profitability and leverage, but divergence in methodology and interpretation. The Z'-Score remains highly valuable as a rapid screening tool, offering intuitive classifications that are straightforward to communicate and apply. The logit model, by contrast, provides greater flexibility, statistical validation, and the possibility of ranking firms along a continuous spectrum of risk. In practice, the evidence suggests that the two frameworks should not be viewed as substitutes but rather as complementary tools: the Z'-Score as a first-pass filter in early screening, and the logit model as a second-stage, probability-based instrument for in-depth due diligence.

5.2 Theoretical and Practical Implications

Theoretical Implications

From a theoretical perspective, the findings of this thesis confirm both the enduring value and the intrinsic limitations of Altman's Z'-Score. More than fifty years after its introduction, the model continues to capture the essence of corporate solvency: profitability and leverage remain the most reliable determinants of default risk. The strong significance of retained earnings to assets and operating profitability to assets in the logit regression reinforces the theoretical robustness of Altman's original intuition. Likewise, the importance of equity relative to liabilities underscores the long-standing principle in corporate finance that capital structure is fundamental to financial resilience.

The ability of the Z'-Score to discriminate between distressed and non-distressed firms, even during a turbulent and atypical period such as the post-COVID years, demonstrates the robustness of its conceptual foundations. Despite profound changes in global capital markets, business models, and macroeconomic conditions, the basic ratios identified by Altman continue to serve as relevant markers of solvency. This consistency echoes the broader academic literature on bankruptcy prediction, which repeatedly finds profitability and leverage to be the most reliable predictors of corporate fragility.

Nevertheless, the analysis also reveals key limitations. Ratios that were central to Altman's original formulation, such as working capital to assets (WC/TA) and sales to assets (S/TA), showed very limited predictive power in this study. Their lack of statistical significance suggests that they are less relevant in the current economic environment, especially when compared to the much stronger explanatory role of profitability and leverage. This is not surprising if viewed in historical perspective. Altman's model was developed in the 1960s, when U.S. manufacturing firms dominated the economy and factors like inventory management, current assets, and turnover efficiency were decisive. By contrast, today's economy is more service-oriented, globalized, and characterized by intangible assets, capital-light structures, and increasingly complex financing arrangements. In this new environment, liquidity and efficiency ratios carry less predictive weight.

Theoretically, this finding supports the growing argument in the academic literature that classical models should not be discarded but recalibrated and complemented with more flexible, data-driven approaches. Logistic regression offers one such alternative. By allowing coefficients to be estimated directly from the dataset under analysis, the logit model avoids the rigidity of fixed weights and static thresholds derived from a very different historical context. Furthermore, the ability to test the statistical significance of each variable adds an extra layer of theoretical robustness, clarifying which financial dimensions remain universally relevant and which have lost explanatory power.

In this sense, the contribution of the logit model is substantial. It demonstrates how modern econometric techniques can extend, rather than replace, classical frameworks. By producing probabilities of default, the logit model transforms financial distress assessment from a categorical classification into a continuous spectrum of risk. This shift reflects contemporary theoretical approaches to risk measurement, which increasingly favor probabilistic and stochastic models over deterministic or threshold-based ones.

Practical Implications for Financial Practitioners

From a practical perspective, the results have equally significant implications for those directly engaged in financial decision-making, such as investment banks, private equity funds, corporate acquirers, credit analysts, and regulators.

In practice, the Z'-Score remains highly valuable as a first-pass tool. Its main advantages lie in its simplicity, transparency, and minimal data requirements. Because it relies exclusively on accounting ratios, it can be computed quickly and applied consistently across very large datasets. This makes it particularly useful during the early phases of M&A screening, when practitioners must evaluate dozens or even hundreds of potential targets under strict time constraints. A distressed Z'-Score immediately signals heightened risk and may either discourage cautious investors or, conversely, attract turnaround specialists who actively seek distressed opportunities.

For more refined due diligence, however, the logit model provides clear additional value. By estimating probabilities of default, it enables decision-makers to move beyond Altman's rigid categories of "safe," "grey," and "distressed." Instead, firms can be placed along a continuum of risk, allowing for far more nuanced investment decisions. For example, two firms might both fall into the grey zone according to the Z'-Score, but the logit model could reveal that one has only a 15 percent probability of default while the other has a 40 percent probability. This distinction, invisible in Altman's framework, is critical for practitioners making high-stakes investment choices.

Another advantage of the logit approach is its flexibility in setting thresholds. Unlike the Z'-Score's static cut-offs of 1.23 and 2.90, thresholds in the logit model can be calibrated depending on context, industry, and investor profile. A conservative strategic acquirer may impose a maximum acceptable probability of default at 10 percent, while a distressed-focused private equity fund may deliberately target firms with probabilities well above that level. This adaptability makes the logit model much more versatile in practice.

Implications for the Nature of M&A Activity

The results also clarify the dual nature of M&A transactions, which has practical importance.

- Rescue-oriented acquisitions involve firms in the distress zone, which are acquired to be restructured, deleveraged, or salvaged. For these transactions, the Z'-Score is particularly effective at flagging high-risk candidates for turnaround strategies.
- Strategic growth acquisitions involve firms with high profitability and robust capital structures. For these transactions, the logit model is especially useful, as it enables investors to quantify relative risks across otherwise healthy firms and to compare them across industries.

Recognizing this duality is crucial for practitioners, since it underscores that the same predictive tools cannot be applied in a uniform way. A distressed-focused investor may view a high probability of default as an attractive opportunity, while a strategic acquirer may treat even moderate risk as unacceptable.

Broader Implications Beyond M&A

The implications of these findings extend beyond M&A into the broader domains of credit risk management and financial regulation. For banks and lenders, the results reaffirm the enduring importance of profitability and leverage as core risk indicators, while cautioning against excessive reliance on liquidity and efficiency ratios. For credit rating agencies, the evidence supports integrating probabilistic models into rating methodologies, particularly in volatile or uncertain environments.

For policymakers and regulators, two key implications emerge. First, stress-testing frameworks should continue to emphasize capital structure and profitability, which consistently prove to be the strongest predictors of resilience. Second, industry-sensitive approaches are required, as uniform thresholds risk overlooking the heterogeneity across sectors and may lead to misclassifications of firms that appear weak in one industry but are structurally stable in another.

5.3 Limitations and Perspectives for Further Research

No empirical study is without limitations, and this thesis is no exception. Acknowledging the boundaries of the analysis is essential not only for transparency but also for providing a foundation for future research in the field of default prediction and M&A risk assessment. The limitations of this work can be grouped into three broad categories: dataset scope, methodological simplifications, and external validity. Each category carries implications for interpretation and naturally points toward areas where further studies could build upon the present findings.

Dataset Limitations

The first limitation concerns the scope and structure of the dataset. The empirical analysis was based on a sample of approximately one hundred firms, which, while meaningful for exploratory purposes, remains relatively modest compared to the scale and diversity of the global M&A market. The limited sample size constrains the statistical power of the results and reduces the ability to generalize conclusions across different contexts.

A more critical issue is that the number of actual default events within the sample was relatively small. Logistic regression requires sufficient variation in the dependent variable to estimate coefficients with precision. When defaults are rare, the model risks producing biased or unstable estimates, particularly for variables with weaker explanatory signals such as working capital to assets or sales to assets. This limitation helps explain why some ratios that are conceptually important in bankruptcy prediction did not emerge as statistically significant in this study. Expanding the dataset to include more defaults would allow for more robust estimates and richer interpretations.

The sectoral distribution of the dataset was also uneven. While industries such as technology and energy were represented by multiple firms, other sectors were covered by only one or two cases. This imbalance complicates the drawing of general conclusions at the industry level, especially in heterogeneous sectors such as materials and real estate. Future research could benefit from constructing sector-specific subsamples, which would enable tailored calibrations that better capture industry dynamics rather than forcing a one-size-fits-all approach.

Methodological Simplifications

The second set of limitations arises from the methodological design of the study. To ensure comparability and replicability, the models were built exclusively on financial ratios calculated from the year immediately preceding the acquisition. This choice, while consistent with Altman's original framework, inevitably excludes several potentially important factors.

First, the analysis did not incorporate macroeconomic indicators. Variables such as interest rate levels, credit spreads, inflation, or GDP growth could influence the probability of default across the sample. Including such measures would help disentangle firm-specific risk from systemic shocks.

Second, no qualitative or governance-related variables were considered. Elements such as board composition, ownership concentration, or managerial quality are widely recognized as factors influencing financial resilience, particularly in the context of acquisitions. Their omission means that the analysis captures only the quantitative dimension of risk, ignoring qualitative aspects that may be highly relevant in practice.

Third, the analysis relied exclusively on accounting data. While accounting ratios are reliable and widely available, they are backward-looking and may fail to capture market perceptions in real time. Forward-looking indicators such as market-implied credit spreads, analyst forecasts, or ESG ratings could provide earlier warning signals of financial fragility. Excluding these variables reduces the model's ability to anticipate emerging risks.

Finally, the choice of logistic regression itself, although justified by its interpretability and established use in the literature, represents a simplification. Logistic regression assumes linear relationships between explanatory variables and the log-odds of default. In reality, financial distress is often driven by complex and nonlinear interactions that may exceed the capacity of such a specification.

External Validity

The third category of limitations concerns external validity. The analysis was explicitly focused on the post-COVID period (2018–2023), chosen for its unique combination of crisis, recovery, and monetary tightening. While highly relevant, this timeframe may not reflect how default predictors behave in other macroeconomic regimes. For instance, variables that proved highly significant during a global pandemic might have less predictive power during extended growth periods or in crises unrelated to health shocks, such as energy disruptions or geopolitical conflicts.

The geographic scope of the dataset was also limited. Most of the firms operate in advanced economies, with only limited representation of emerging markets. Because default dynamics can differ significantly in emerging economies—due to differences in capital market development, legal frameworks, and macroeconomic volatility—the findings cannot easily be generalized to those contexts. Expanding the analysis to such markets would be essential for testing robustness.

Industry representation was also incomplete. Several sectors that play a major role in M&A activity, such as financial institutions, telecommunications, and utilities, were not extensively covered. These industries have structural features, such as regulation, capital intensity, and stable revenue models, that may alter the predictive relevance of traditional ratios. A more balanced sectoral representation would therefore enhance the external validity of the results.

Perspectives for Future Research

These limitations open up a range of avenues for further research that could enrich the field both theoretically and practically:

1. Dataset Expansion. Enlarging the dataset in terms of both time horizon and geographic coverage would improve statistical power and increase representativeness. A broader sample would also allow for the calibration of sector-specific models that better capture heterogeneity across industries.
2. Longer Observation Windows. Extending the observation period beyond the year preceding the acquisition would provide insight into how multi-year trends in profitability or leverage affect default risk. Incorporating post-acquisition outcomes over longer horizons (e.g., three to five years) would also help evaluate whether models predict not only immediate distress but also medium-term underperformance.
3. Integration of Additional Variables. Future studies could incorporate macroeconomic indicators (such as interest rates, credit spreads, or volatility indices), qualitative measures (such as governance quality or ownership structures), and forward-looking metrics (such as analyst forecasts or ESG ratings). These would allow for a more holistic framework that blends accounting data with broader dimensions of corporate health.
4. Alternative Modeling Approaches. Advanced statistical and machine learning methods—such as random forests, gradient boosting, support vector machines, or neural networks—could be applied to capture nonlinearities and complex interactions that logistic regression may overlook. Survival analysis techniques could also be used to model not only the probability but the expected timing of default.
5. Comparative Evaluations. Further work could compare the performance of Altman's model, logit regression, and machine learning approaches on the same dataset, quantifying the trade-offs between interpretability, precision, and flexibility. Such comparisons would provide practical guidance on which tool is most appropriate depending on the context.
6. Policy and Regulatory Applications. Extending the analysis to regulatory settings would test how well accounting-based models perform in stress testing and early warning systems. This line of research could assess whether simple ratio-based models suffice for systemic monitoring or whether more complex frameworks are required to anticipate large-scale defaults.

In sum, while this thesis provides valuable evidence on the continued relevance of Altman's Z'-Score and the added value of a logit model, its limitations suggest clear opportunities for future research. By expanding datasets, integrating broader variables, and experimenting with advanced methodologies, future studies can further refine the tools available for predicting default and assessing financial risk in the context of M&A.

5.4 Final Remarks

In conclusion, this thesis has addressed one of the most enduring and debated questions in corporate finance: how to reliably predict the risk of corporate default, particularly in the delicate and high-stakes context of mergers and acquisitions (M&A). The empirical analysis shows that while traditional bankruptcy prediction tools remain valuable, they must evolve to remain effective in today's financial environment. The findings confirm that Altman's Z'-Score continues to provide meaningful insight into financial health, yet they also highlight the superior flexibility, adaptability, and statistical rigor of logistic regression when applied to the same financial ratios. By combining a familiar, interpretable benchmark with a probability-based econometric framework, the study demonstrates how practitioners can improve ex-ante risk assessment without sacrificing transparency.

A Balanced View on Tradition and Innovation

The evidence indicates that the future of default prediction does not lie in abandoning traditional models, nor in adopting modern methods uncritically. Rather, the most effective approach is to integrate tradition and innovation in a complementary way. The Z'-Score, despite being developed more than fifty years ago, demonstrates remarkable resilience: it consistently differentiates between distressed and financially healthy firms across a broad and diverse sample and remains sensitive to macro-financial cycles. Its ability to flag genuine default cases—such as Hertz or Seadrill—speaks to the robustness of Altman's original intuition and to the continued relevance of profitability- and leverage-centered diagnostics.

At the same time, the study makes clear that the Z'-Score alone is not sufficient. Fixed thresholds and historically estimated coefficients are blunt instruments in a global economy where business models evolve rapidly, capital structures are more complex, and external shocks—from pandemics to inflationary cycles—reshape risk profiles in real time. Logistic regression addresses these limitations. By estimating coefficients directly from the data, the logit model aligns with current evidence and produces firm-level default probabilities rather than categorical labels. This enables users to calibrate cut-offs to risk appetite, sectoral conditions, and strategic objectives, and to update parameters as new data arrive—capabilities that are indispensable for a living risk framework.

Implications for Theory

From a theoretical standpoint, this thesis validates a core principle of financial economics: profitability and leverage remain the foundation of corporate solvency analysis. Decades of research have shown that firms with strong earnings and conservative capital structures are less likely to default; the present results reaffirm this view in a post-COVID setting. At the same time, the weaker predictive power of liquidity and asset-turnover ratios indicates that theoretical frameworks must evolve alongside economic realities. Intangible-intensive, service-oriented, and platform-based models render working-capital intensity and sales-to-assets less diagnostic of default risk than they were in inventory-heavy manufacturing economies.

These findings align with recent literature advocating recalibration and complementarity: keep the signal-rich ratios (cumulative and operating profitability, market-based leverage), and subject weaker components to empirical scrutiny within each context. The logit framework operationalizes this stance by providing statistical tests of relevance, dataset-specific coefficients, and probability outputs. Conceptually, migrating from deterministic thresholds to a continuous risk spectrum mirrors the broader shift in modern finance toward stochastic and scenario-based risk measurement.

Implications for Practice

For M&A practitioners, investment banks, private equity funds, corporate acquirers—the implications are concrete and implementable.

- First-pass screening. Use the Z’-Score to triage large universes quickly, frame the deal thesis (turnaround versus strategic growth), and prioritize diligence resources.
- Second-stage due diligence. Deploy the logit model to quantify probability of default (PD), rank otherwise similar targets, and tailor thresholds to mandate and sector. A “grey-zone” target with PD ≈ 15% is a different proposition than one at 40%.
- Deal design and monitoring. Probability-based outputs support pricing, leverage sizing, covenant design, and post-close monitoring (e.g., PD triggers for remediation). PDs can also inform synergies-at-risk and sensitivity analyses in integrated valuation models.
- Portfolio construction. For buyout funds and corporate acquirers with multiple simultaneous deals, PDs enable risk-budgeting across targets, geographies, and cycles, and help set hurdle rates and risk-adjusted IRR expectations.

The dual nature of M&A

- Rescue-oriented transactions. The Z’-Score is efficient at flagging high-risk candidates for restructuring and operational turnarounds; PDs help discriminate recoverable distress from structural fragility.
- Strategic growth transactions. Among healthy targets, the logit model provides a nuanced ranking of residual risk that improves selection among close substitutes and supports disciplined overpayment avoidance.

Broader Relevance

Beyond M&A, the findings carry wider significance for banks, credit investors, rating agencies, and regulators.

- Banks and credit investors. Retain profitability and capital structure as core indicators; contextualize liquidity and turnover by sector. Use PDs for limit-setting, pricing grids, and early-warning overlays.
- Rating agencies. Integrate probability-based signals to augment accounting models in volatile regimes and to increase transparency around ratings watch/transition dynamics.
- Regulators and policymakers. In stress testing and early-warning systems, continue to emphasize earnings power and capitalization, but adopt industry-sensitive calibration to avoid threshold-driven misclassification across heterogeneous sectors.

Link to Robustness and Validation

In line with best practice, the thesis included robustness checks and model validation (Chapter 4.7), showing that the core results are stable across subsamples and cut-offs, and are consistent with ROC–AUC and classification-matrix evidence. While AUC does not capture all aspects of economic utility, it corroborates the logit model’s discriminative capacity and supports the complementary use of Z’-Score and logit for screening and prioritization.

Achievement of the Thesis Objective and Closing Reflection

Most importantly, the thesis achieves its stated objective: to evaluate the continued relevance of Altman’s model and to assess the added value of a logit approach in the post-COVID context. The analysis shows that Altman’s ratios remain valid indicators of financial health, but their relative importance has shifted, with profitability and leverage dominant and liquidity/efficiency secondary.

The logit model adds statistical validation, adaptability, and decision-ready PDs, making it more effective for modern applications without sacrificing interpretability.

More broadly, the thesis underscores that financial risk assessment is not static. The COVID-19 shock, and the rapid policy and market transitions that followed, reminds scholars and practitioners of the need for models that both generalize across time and update with new information. The most effective path is not to choose between traditional and modern approaches, but to combine the interpretability of classical models with the adaptability of probabilistic econometrics.

By following this integrated approach, financial decision-makers can better navigate uncertainty, distinguish distressed from resilient firms, and increase the likelihood of successful acquisition outcomes. In this sense, the thesis functions as both a reaffirmation of enduring insights and a call to innovate, advocating pragmatic, data-informed tools that are rigorous enough for academia and practical enough for the deal room.

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