Evaluating the Accuracy of Valuation Models: Evidence from U.S. Listed Firms and Hybrid Approaches

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ABSTRACT

This thesis evaluates the accuracy of four major valuation models: Discounted Cash Flow (DCF), Residual Income Model (RIM), Net Asset Value (NAV) and Multiples, using a sample of 494 U.S. listed firms. It tests how close each method gets to the real market values and if combinations of them into hybrid frameworks can improve the predictive performance. Data are gathered from Compustat, CRSP, I/B/E/S and Damodaran databases. The accuracy of the models is assessed through Mean and Median Absolute Percentage Errors complemented by a fundamentals-based valuation model that links market-to-book ratios to firm profitability, leverage, risk, growth and size. The results show that RIM is systematically outperforming DCF, NAV has the weakest performance but is still relevant in asset-heavy industries, and Multiples yield competitive accuracy in homogeneous sectors. Firm profitability and growth are positively correlated with the market-to-book ratio, while leverage has a strong negative effect. The hybrid valuation models had reduced errors compared to NAV and Multiples, but they do not consistently outperform the RIM model out-of-sample. Overall, the findings highlight the challenges that firm-level valuation poses and show that by combining different valuation models the substantial deviations inherent in traditional valuation approaches are not eliminated, but stability is improved.

Table of Contents

1. INTRODUCTION **4**

2.LITERATURE REVIEW **6**

2.1 Empirical Evidence on Valuation Accuracy 6
2.2 Firm-Specific Drivers of Market Valuation 8
2.3 Combined and Hybrid Approaches 9
2.4 Synthesis and Hypotheses 10

3. DATA **12**

3.1 Institutional features of the U.S. market 12
3.2 Data sources and sample construction 12
3.3 Descriptive statistics 14

4. EMPIRICAL METHODOLOGY **18**

4.1 Overview 18
4.2 Valuation Models Accuracy 19
4.2.1 Discounted Cash Flow (DCF) *19*
4.2.2 Residual Income Model (RIM) *20*
4.2.3 Net Asset Value (NAV) *21*
4.2.4 Multiples *22*
4.3 Accuracy Measurement 22
4.4 Statistical Testing of pricing errors 23
4.5 Fundamentals-based valuation model 24
4.6 Combination of Methods 26

5. RESULTS **28**

5.1 Valuation accuracy across models 28
5.2 Industry-level accuracy differences 30
5.3 Fundamentals-based valuation model 33
5.3.1 Model regression *33*
5.3.2 Predictive accuracy of the Fundamentals-based model *36*
5.4 Combination of Methods 39

6. CONCLUSION **43**

7. REFERENCES **45**

8. APPENDIX **47**

9. ACKNOWLEDGEMENT OF AI USE **55**

1. Introduction

The accurate estimation of a firm's intrinsic value remains one of the most fundamental challenges in corporate finance. Even though there has been extensive development of valuation methodologies over the past decades, there is still no verdict regarding which model provides the most reliable approximation of market value. The aim of this thesis is to investigate how accurately the main valuation models are capturing the market value of listed firms and test whether a combination of these different methods (hybrid models) can lead to improved predictive performance. The analysis aims to offer empirical evidence on the comparative accuracy of the Discounted Cash Flow (DCF), Residual Income Model (RIM), Net Asset Value (NAV) and Multiples valuation methods, and to examine whether hybrid combinations of these models lead to lower valuation errors.

Valuation plays a central role in both investment decisions and corporate transactions, which makes this topic highly relevant for both academics and practitioners. Theoretical models often rely on simplifying assumptions that fail to capture market realities, while practitioners are frequently relying on subjective adjustments that can distort objectivity. Evaluating the empirical accuracy of valuation models is therefore contributing to bridging the gap between academic theory and professional application, particularly in an environment where market prices reflect a combination of firm fundamentals, risk expectations and behavioral components.

The empirical analysis is conducted on a sample of 494 publicly listed U.S. companies covering all major industries. Financial statement data have been obtained from Compustat, market data from CRSP, analyst forecasts from I/B/E/S and sector-level parameters from the Damodaran database. The U.S. market provides an ideal setting for such an analysis, given its size, liquidity and extensive disclosure requirements, which ensure both data availability and comparability across firms and sectors.

This study follows a three-stage empirical framework. First, four traditional valuation methods (DCF, RIM, NAV, Multiples) are applied to each firm to estimate intrinsic equity values. Their predictive accuracy is then evaluated using the Mean Absolute Percentage Error (MAPE) and the Median Absolute Percentage Error (MdAPE), which capture both average and median deviations from observed market capitalization. Second, fundamentals-based valuation model is estimated by relating market-to-book ratio to firm characteristics such as profitability, leverage, risk, growth

and size. This model is then used to generate implied equity values and evaluated with the same accuracy metrics, providing a benchmark for how well fundamentals alone can explain market valuations. Third, the analysis tests whether integrating multiple valuation approaches into hybrid models can enhance the overall predictive accuracy.

The main results show that RIM systematically outperforms the DCF approach, confirming earlier findings by Penman and Sougiannis (1998) and Francis, Olsson and Oswald (2000). The NAV method performs the weakest overall but remains useful in asset-intensive industries, while Multiples demonstrate competitive median accuracy when applied to homogeneous sectors. Furthermore, the fundamentals-based model indicates that firm profitability and expected growth are positively associated with market valuations, while leverage has a strong negative effect, but its overall predictive accuracy remains limited, particularly out-of-sample. When the valuation methods are combined, the hybrid models reduce valuation errors relative to several standalone approaches (especially NAV and Multiples), but they do not consistently outperform the RIM model out-of-sample. The dynamically weighted hybrid delivers strong improvements in-sample but exhibits signs of overfitting when applied to unseen observations. These findings suggest that hybrid frameworks help mitigate method-specific weaknesses but do not surpass the strongest individual benchmark, consistent with the broader conclusions of Cavezzali and Rigoni (2013) and Gao (2019) regarding the benefits and limitations of integrated valuation perspectives.

The rest of the thesis is organized as follows. Section 1 reviews the relevant literature and outlines the theoretical background of these valuation methods examined. Section 2 describes the data sources, sample construction and industry classification. Section 3 presents the empirical methodology, including valuation models, regression framework and hybrid weighting schemes. Section 4 reports and interprets the empirical results. Finally, Section 5 concludes by summarizing the main findings, discussing limitations and suggesting possible future research.

2.Literature Review

The main aim of valuation research is to evaluate how accurate different models are at capturing the intrinsic value of firms relative to observed market prices. Even though discounted cash flow (DCF), residual income models (RIM), net asset value (NAV) and multiples are the most well-known approaches in practice, their empirical accuracy has been shown to vary considerably. This literature review shows the most relevant contributions to the field, explaining the methods tested and their empirical results.

2.1 Empirical Evidence on Valuation Accuracy

Francis, Olsson and Oswald (2000) examined 3000 firm-year observations of US companies using Value Line forecasts between 1989 and 1993 to test the dividend discount, free cash flow and abnormal earnings (= residual income) models. They evaluated the methods along two dimensions: accuracy, measured by the median absolute percentage error (MdAPE) relative to market prices, and explainability, measured by the proportion of price variation explained. They reached the result that the residual income model outperformed the other approaches, producing a median error of 30% compared to 41% for free cash flow and 69% for dividends. Abnormal earnings models also explained 71% of price variation, while free cash flows did 35% and dividends did 51%. They attributed this superiority to the reduced reliance on terminal values, which accounted for just 21% of residual income valuations compared to 82% in free cash flows and 65% in dividend models. These results provide strong support for residual income approaches and show the need for professionals to evaluate the predictive accuracy of each valuation method before using them in practice.

The work of Penman and Sougiannis (1998) is closely related to the previous research. They directly compared dividend, cash flow and residual income models using realized fundamentals. Again, residual income method was proved to be the most accurate one, with significantly smaller valuation errors than DCF or dividend discount models. This result was explained by the authors by emphasizing that residual income's anchoring in book value and short-term earnings reduces the dependence on uncertain, long-term forecasts, which mitigates compounding errors. This theoretical reasoning and empirical evidence worked as a steppingstone for later studies such as Francis et al. (2000), strengthening the case for residual income as a superior valuation model in terms of accuracy.

Turning to discounted cash flow methods, Kaplan and Ruback (1995) provided one of the earliest systematic evaluations of DCF accuracy in practice. They used a dataset of leveraged buyouts and management forecasts and compared DCF estimates to actual transaction values. What they found out was that median DCF estimates were within 10% of deal prices, which could mean that the method can be reliable when high-quality forecasts are available. However, they also reported substantial firm-level deviations, with individual valuation errors exceeding the median by a lot. Their study is important because it highlights both the strength and weakness of DCF. Under ideal conditions it can be quite precise, but its heavy reliance on long-horizon forecasts and terminal assumptions makes it vulnerable to large errors in broader applications.

Even though much of the literature contrasts DCF and residual income models, Lie and Lie (2002) decided to investigate the accuracy of another method, the multiples. They conducted a large-sample analysis of multiples such as P/E (Price to Earnings), EV/EBITDA (Enterprise Value to EBITDA) and P/S (Price to Sales), and they found out that EV/EBITDA consistently produced smaller valuation errors than other ratios, while P/E was the least accurate. Furthermore, they showed that getting the average of several multiples leads to an increase in accuracy, compared to using a single ratio. Their findings highlight the implementation sensitivity of multiples and suggest that some ratios carry more informational content than others.

Bhojraj and Lee (2002) took that research one step further by examining how the accuracy of multiples is influenced by the selection of comparable firms. They realized that traditional industry-based peer groups often fail to capture relevant valuation drivers and proposed peer matching based on value drivers instead. Their empirical results show that valuations based on comparables chosen for similarity in fundamentals were significantly more accurate than those based on industry classification alone. These findings show that the peer selection process has just as much impact on multiples accuracy as the ratio selection.

The Net Asset Value method is less frequently emphasized in capital markets research, but it remains relevant, especially for asset-intensive firms. NAV values equity as the difference between assets and liabilities, adjusted to reflect fair values. Fernández (2007) in his research points out that NAV will systematically undervalue firms that possess substantial intangible assets of growth opportunities, since it ignores the future earnings potential and goodwill. This critique is supported by empirical evidence from Cavezzali and Rigoni (2013). By examining analyst reports, they

found that NAV-based valuations were one of the least accurate approaches when benchmarked against market prices. With that in mind, they mentioned that NAV is still relevant in practice in specific contexts. In another paper, Grandis and Palazzi (2015) highlight its usefulness in financial institutions and real estate firms, since these are entities where tangible assets are very important for value creation. Similarly, Trugman (2017) notes that NAV can serve as a lower-bound estimate or liquidation value, especially for distressed companies. This exactly is the reason why, even though NAV may underperform in tests of accuracy for the broad market, it remains an important benchmark for certain industries and is included in this thesis.

2.2 Firm-Specific Drivers of Market Valuation

Evaluating the accuracy of different valuation methods is a topic that many researchers have tried to investigate. To do so, it is also important to understand the broader economic context in which valuations take place. Market prices show how investors assess firms' fundamentals, potential growth opportunities and risk associated with them. Building on this idea, the existing literature also examines the underlying factors that shape firm equity value, on top of the performance of the different valuation models.

The literature highlights that a firm's market value does not only depend on the choice of the correct model, but on financial and structural factors as well. Forecast quality and horizon are central. Francis et al. (2000) showed that free cash flow and dividend models rely a lot on terminal values, often exceeding 80% of estimated firm value and makes them prone to errors. In contrast, residual income models are not reliant on long-horizon forecasts by anchoring in book values and short-term earnings (Penman & Sougiannis, 1998).

Discount rate estimation is another key factor. Fernández (2007) reported recurring errors in WACC calculations, such as mixing real and nominal inputs, which generate major inaccuracies in DCF valuations. Comblain (2021) emphasized that small firms often require a size premium in the cost of equity to adequately capture risk, but this adjustment is frequently overlooked in practice.

Two factors that are quite significant are firm size and liquidity. In their research, Rodríguez-Valencia, Lamothe-Fernández and Alaminos (2023) compared valuations of private and listed SMEs and found systematic differences in their accuracy because of liquidity constraints that led to discounts in private firm valuations. In a similar study, Klunder (2016) reported that forecast

quality and negotiation dynamics play an important role in the divergence between theoretical valuation results and observed transaction prices in small and medium enterprises (SMEs).

Other performance influencers are industry structure and asset composition. Grandis and Palazzi (2015) noted that NAV is relatively more accurate in asset-heavy sectors, while Bhojraj and Lee (2002) found out that multiples perform best when applied to homogeneous industries with carefully chosen comparables. Finally, intangible assets play a role as well. Francis et.al (2000) discovered that residual income models retained their accuracy even in high-R&D firms, but Vallejo-Alonso, García-Merino and Arregul-Ayastuy (2015) argue that intangibles often escape reliable measurement, limiting the precision of accounting and multiples-based valuations.

2.3 Combined and Hybrid Approaches

Accuracy rankings of valuation models also depend on methodological choices, as shown by Dittmann and Maug (2008). According to them, the relative performance of discounted cash flow, residual income and multiples changes depending on whether mean squared errors, mean absolute errors, or percentage-based measures are used. When mean absolute percentage error (MAPE) is applied (as in this thesis) residual income and multiples outperform DCF in many cases. They also emphasized that no single error metric perfectly captures accuracy, which calls for robustness checks across multiple measures.

The use of multiple methods in combination has also been studied in the context of analyst reports. Cavezzali and Rigoni (2013) analyzed over 1600 equity research reports for their research and came to the conclusion that target prices which were derived from a combination of methods were systematically more accurate than those based on a single model. They discovered that analysts who used all three main methods (discounted cash flows, residual income and multiples) reduced their valuation errors significantly. This result supports the idea that hybrid approaches, which diversify model-specific biases, may yield superior accuracy compared to standalone techniques.

Gao (2019) with his work helped at formalizing the idea of hybrid valuation by combining dividend discount, residual income and multiples into regression-based models. By testing on a broad sample, he found that hybrid methods outperformed individual approaches in terms of reducing valuation error. His results provide evidence that if you systematically weight the outputs of multiple models, you can deliver more accurate predictions of market values than by using any single model. This study extends earlier evidence from analyst practice (Cavezzali and Rigoni,

2013) and error-metric analysis (Dittmann and Maug, 2008) by offering a structured framework for hybrid valuation. All these findings suggest that hybrid approaches offer a promising avenue for improving valuation accuracy across firms and industries.

2.4 Synthesis and Hypotheses

By reviewing the literature, we get some clear insights. Firstly, residual income models tend to outperform DCF and dividend models in terms of accuracy in a consistent way, with evidence from both Penman and Sougiannis (1998) and Francis et al. (2000) supporting this. The DCF method can deliver accurate results when there are reliable forecasts available, but it is dependent on terminal assumptions, which makes it less robust in large samples (Kaplan & Ruback, Fernández). Multiples approach provides competitive results, particularly when comparables are carefully selected and ratios are combined (Lie & Lie, Bhojraj & Lee). Moreover, NAV method generally performs poorly in broad-market settings but remains relevant for asset-heavy sectors and distressed firms (Fernández, 2007; Grandis & Palazzi, 2015). Beyond model choice, factors such as firm size, risk, liquidity, industry structure and intangibles play an important role in shaping the market value of a company. Finally, evidence suggests that combining methods or constructing hybrids may help at reducing the error further (Dittmann & Maug, Cavezzali & Rigoni, Gao).

Based on these findings, this thesis formulates the following hypotheses:

Accuracy across models:

- H1: RIM outperforms DCF in terms of accuracy because it anchors valuations in book value and near-term earnings.
- H2: NAV performs better than other methods in asset-heavy sectors (e.g. financials, real estate), but performs much worse in intangible-intensive industries (e.g. technology)
- H3: Multiples achieve competitive accuracy, but their performance depends critically on peer selection and industry homogeneity.

Fundamentals-based valuation model

- H4: A fundamentals-based regression model predicting market-to-book ratios from firm characteristics provides valuation accuracy comparable to traditional valuation methods.

Combination of Methods

- H5: Combining traditional valuation methods into a hybrid valuation model achieves higher accuracy than the individual standalone methods.

3. Data

3.1 Institutional features of the U.S. market

The empirical setting for this thesis is the U.S. equity market, which is the largest and most liquid stock market worldwide. U.S. exchanges, primarily NYSE and NASDAQ, list thousands of companies that belong to all major industries. This creates a rich environment that allows the firms that will be picked to test the relative accuracy of different valuation models to vary in terms of size, profitability, leverage, risk and growth opportunities.

A key institutional feature of the U.S. market is its strong disclosure regime. Firms that are publicly traded are required by SEC to file quarterly and annual reports under U.S. Generally Accepted Accounting Principles (GAAP). These reports, which are audited by independent entities, provide financial statements that have a standard format and therefore enhance the comparability and reliability of firm-level data. Furthermore, the U.S. market is covered by high levels of analysts, and many investors participate in it, making it relatively efficient. This means that observed market valuations serve as a credible benchmark against which we can compare model-based estimates.

The diversity of the firms contained in the U.S. equity market also highlights the challenges for empirical valuation research. Firms differ in terms of business models, capital structure and exposure to risk, meaning that no single valuation model can be expected to perform equally well across the entire market. Such a heterogeneous environment makes testing valuation accuracy both informative and demanding.

3.2 Data sources and sample construction

The analysis draws data on both firm and industry level from established sources. Firm-level financial statement variables, such as EBIT, net income, capital expenditures, depreciation, total assets, total debt and book equity were obtained from Compustat, while market related data such as stock prices and market capitalization were drawn from CRSP. In order to implement DCF and RIM valuation methods, forecast data for future earnings, cash flows and dividends were also required, using 2024 as the base year. These data were drawn from I/B/E/S, a database that collects and aggregates analyst forecasts of many financial indicators for U.S listed firms, ensuring that the forecasts reflect market consensus rather than the projections of a single institution. All these databases were available in WRDS, for which Tilburg University has provided access.

Industry-level data were obtained from the Damodaran database, which supplies sector averages for valuation multiples, equity betas and cost of capital estimates. The firms from our sample were mapped to industries using a SIC to Damodaran conversion, ensuring that each firm was consistently linked to appropriate sector benchmarks.

The original dataset covered several thousand of U.S. listed firms. However, the joined requirement of both complete financial statement data and forecast data limited the sample to only 494 U.S. firms. In order to ensure data consistency, it was necessary to apply some restrictions. Firms are required to have non-missing values for all key variables used in the valuation models, including 3-year forecast data for cash flows, dividends, earnings, net income, capital expenditures and long term growth, as well as current sales, net income, total assets, book equity, total debt, cash holdings, interest expense, tax rate, beta and market capitalization. Second, firms with negative book equity in 2024 are excluded, since negative equity renders NAV and residual income calculations meaningless. Third, at least one year of positive forecast net income is required in order to remove firms that are expected to remain loss making throughout the entire forecast horizon.

Additional filters are applied to eliminate extreme or implausible forecast profiles. Observations with excessively large year -to-year jumps in cash flows between forecast years are removed by requiring that the absolute change between consecutive periods remains below 400%. This threshold eliminates cases in which forecasted cash flows increase or decrease by more than a factor of four in a single year. Such changes are highly uncommon for mature publicly listed companies and generally indicate data errors or extraordinary events. Also, forecast capital expenditures must be non-negative and less than 30% of a firm's current market capitalization, to prevent implausibly large investment plans that would distort DCF valuation through inflated FCFE trajectories and terminal values. Finally, firms are also required to have strictly positive total debt in 2024 in order to ensure well-defined leverage and enterprise value calculations.

The remaining dataset of 494 firms covers all major sectors of the U.S. market. By combining the financial data of the companies (Compustat & CRSP), analyst expectations (I/B/E/S) and the industry-level data (Damodaran), a comprehensive basis for testing the accuracy of different valuation models has been created.

3.3 Descriptive statistics

This section presents summary statistics for the sample of 494 U.S. listed firms with complete financial and market information. The variables reported in Table 1 are drawn from Compustat and CRSP and represent the core firm-level measures used in the regressions.

Table 1: Descriptive Statistics — Valuation Inputs (Compustat & CRSP)

Variables	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
Beta	494	1.20	0.49	0.44	1.14	2.10
Book Equity (USD mn)	494	11219.08	28127.86	416.83	3622.15	41131.70
Capital Expenditures (USD mn)	494	1329.06	5306.84	10.12	262.24	4449.55
Cash & Equivalents (USD mn)	494	2811.85	8362.34	55.36	762.67	10906.52
Change in Working Capital (USD mn)	494	-79.63	1938.16	-2098.40	-3.78	1861.36
Depreciation (USD mn)	494	1129.96	2877.55	24.32	334.50	4034.65
EBITDA (USD mn)	494	3973.21	10321.36	51.65	1189.85	14587.00
Employees	494	32	82	1	13	111
Enterprise Value (USD mn)	494	55597.33	157419.27	1674.69	15521.44	199182.08
Interest Expense (USD mn)	494	398.95	861.57	1.31	156.04	1447.00
Market Capitalization (USD mn)	494	49048.62	154137.84	1220.45	12357.91	170722.35
Net Debt (USD mn)	494	6548.71	16845.05	-1595.12	2173.64	29802.91
Net Income (USD mn)	494	1858.45	6616.95	-453.67	489.39	6628.70
Operating Income after Depreciation (USD mn)	494	2843.24	7899.29	-21.59	822.00	10158.65
Sales (USD mn)	494	20217.98	51233.89	685.40	6345.80	81015.20
Share Price (USD)	494	123.72	145.68	9.84	73.94	418.75
Shares Outstanding (mn)	494	466.98	1010.88	40.19	189.58	1705.01
Total Assets (USD mn)	494	29878.80	61766.49	1237.63	9902.10	118843.40
Total Debt (USD mn)	494	9360.56	19706.66	66.76	3181.00	35435.92
Total Liabilities (USD mn)	494	18259.41	37526.31	487.93	5702.40	77170.85
WACC	494	0.09	0.02	0.06	0.09	0.12

Note: The table reports descriptive statistics for the final sample (N = 494). All monetary variables are in millions of USD. Variables include only Compustat and CRSP inputs used in the valuation models (DCF, RIM, NAV, Multiples). WACC is constructed from firm accounts and market inputs; the risk-free rate and equity risk premium are constant across firms.

Table 2 reports the distribution of sample firms across the Damodaran industry groups for 2024, along with the EV/EBITDA multiple associated with each one:

Table 2: Damodaran Industries — Sample Coverage and EV/EBITDA for 2024

Industry (Damodaran)	N Obs	EV/EBITDA
Advertising	4	12.94
Aerospace/Defense	11	18.49
Air Transport	3	6.17
Apparel	5	7.92
Auto & Truck	6	21.65
Auto Parts	7	7.06
Bank (Money Center)	0	-
Banks (Regional)	0	-
Beverage (Alcoholic)	4	14.84
Beverage (Soft)	3	18.07
Broadcasting	6	7.31
Brokerage & Investment Banking	5	-
Building Materials	3	12.01
Business & Consumer Services	9	16.12
Cable TV	2	7.8
Chemical (Basic)	5	8.1
Chemical (Diversified)	0	15.4
Chemical (Specialty)	14	12.85
Coal & Related Energy	0	2.75
Computer Services	44	12.61
Computers/Peripherals	3	21.83
Construction Supplies	3	11.12
Diversified	2	8.93
Drugs (Biotechnology)	13	13.52
Drugs (Pharmaceutical)	14	16.62
Education	2	10.8
Electrical Equipment	5	14.65
Electronics (Consumer & Office)	0	19.14
Electronics (General)	10	13.59
Engineering/Construction	3	12.76
Entertainment	4	16.37
Environmental & Waste Services	5	15
Farming/Agriculture	2	8.97
Financial Svcs. (Non-bank & Insurance)	8	62.48
Food Processing	8	12.51
Food Wholesalers	2	11.26
Furn/Home Furnishings	5	9.37
Green & Renewable Energy	0	12.63
Healthcare Products	21	21.51

Industry (Damodaran)	N Obs	EV/EBITDA
Healthcare Support Services	15	11.29
Healthcare Information and Technology	15	21.44
Homebuilding	0	7.79
Hospitals/Healthcare Facilities	4	8.75
Hotel/Gaming	11	14.98
Household Products	3	15.95
Information Services	0	12.15
Insurance (General)	6	11.48
Insurance (Life)	0	17.24
Insurance (Prop/Cas.)	0	11.77
Investments & Asset Management	2	34.85
Machinery	21	15.46
Metals & Mining	8	10.36
Office Equipment & Services	0	9.34
Oil/Gas (Integrated)	0	6.24
Oil/Gas (Production and Exploration)	21	4.67
Oil/Gas Distribution	5	7.31
Oilfield Svcs/Equip.	20	5.42
Packaging & Container	8	8.63
Paper/Forest Products	1	7.06
Power	6	11.69
Precious Metals	10	13.01
Publishing & Newspapers	1	10.52
R.E.I.T.	3	21.02
Real Estate (Development)	0	17.93
Real Estate (General/Diversified)	0	18.01
Real Estate (Operations & Services)	4	14.98
Recreation	3	9.99
Reinsurance	0	7.28
Restaurant/Dining	4	16.6
Retail (Automotive)	6	11.63
Retail (Building Supply)	2	13.33
Retail (Distributors)	7	11.63
Retail (General)	0	16.63
Retail (Grocery and Food)	2	6.38
Retail (REITs)	0	17.43
Retail (Special Lines)	6	9.34
Rubber& Tires	0	7.95
Semiconductor	9	31.59
Semiconductor Equip	3	18.18
Shipbuilding & Marine	3	8.38
Shoe	3	18.95
Software (Entertainment)	0	17.16
Software (Internet)	0	19.33

Industry (Damodaran)	N Obs	EV/EBITDA
Software (System & Application)	13	28.43
Steel	4	5.93
Telecom (Wireless)	5	9.01
Telecom. Equipment	2	13.98
Telecom. Services	1	6.18
Tobacco	0	10.84
Transportation	4	12.01
Transportation (Railroads)	3	14.32
Trucking	9	10.57
Utility (General)	0	11.7
Utility (Water)	0	16.86

Note: N Obs is the number of firms in the final sample mapped to each Damodaran industry. EV/EBITDA values are taken from the Damodaran multiples file.

Such a long list of industries is quite helpful to perform the Multiples valuation method but is not very useful when the time to start the comparisons comes. For this reason, after the calculations, these categories were grouped into 10 large industry groups, which are shown in table 3 below:

Table 3: Broad Industry Categories for 2024

Broad Category	N.Obs
Technology, Media & Telecom	103
Healthcare	82
Industrials	82
Consumer Goods	70
Energy & Utilities	52
Basic Materials	42
Financials	28
Food & Beverages	17
Hotels, Leisure & Gaming	11
Environmental & Agriculture	7

4. Empirical Methodology

4.1 Overview

This chapter describes the empirical framework adopted to evaluate the accuracy of valuation models and the determinants of enterprise value. The analysis follows a structured three-stage approach.

Firstly, four valuation techniques (Discounted Cash Flow (DCF), Residual Income Model (RIM), Net Asset Value (NAV) and Multiples) are implemented to estimate firm-level intrinsic values using data from Compustat, CRSP, I/B/E/S and Damodaran databases. Each model represents a different theoretical approach to company valuation that ranges from forward-looking discounted cash flows to accounting based or relative methods. After the model-based values of the companies are calculated, they are compared to the observed market valuations and the Median Absolute Percentage Error (MdAPE) is computed for each method, which illustrates the deviations between the two.

Secondly, the analysis introduces a fundamentals-based valuation model that estimates firms' market-to-book (M/B) ratios from observable financial characteristics. This regression-based approach serves as an additional valuation method, allowing comparison with the traditional models. The model includes industry fixed effects to account for sector-level heterogeneity. By linking firm fundamentals (size, leverage, risk, growth and profitability) to market valuation, this analysis evaluates whether a cross-sectional fundamentals model can predict market values with comparable accuracy.

Thirdly, a hybrid valuation model is constructed by combining the outputs of the different valuation models in a weighted framework to evaluate whether an integration of methods can lead to more accurate results. Three hybrid versions are examined: an equal weight benchmark, an accuracy-weighted model based on training-sample performance, and a dynamic model whose weights vary with firm characteristics and are validated out-of-sample.

This three-step design provides a coherent empirical basis for evaluating how and why valuation performance varies across methods and firms.

4.2 Valuation Models Accuracy

The implementation of the four valuation models follows standard formulations adapted to the data available for each firm. All calculations are performed in R and expressed in millions of U.S. dollars.

Before applying the individual models, several global parameters are established in order to ensure consistency across the valuations. The risk-free rate (rf) is set at 4%, approximating the yield of the 10-year U.S. Treasury bond in early 2024 (Damodaran, 2024). The equity risk premium is set at 5%, in line with the long-run U.S. market average reported by Damodaran (2024) and Fernández et al. (2011). The terminal growth rate (g) is fixed at 2.5% and reflects the expected long-term nominal growth of the U.S. economy. It is consistent with the valuation practice that perpetual growth should not exceed gross domestic product (GDP) growth.

4.2.1 Discounted Cash Flow (DCF)

The DCF approach estimates the intrinsic value of equity as the present value of future free cash flows to equity (FCFE). It is a forward-looking method based on the principle that a firm's value is equal to the cash flow available to the shareholders, discounted at their required rate of return.

$$Value_i^{DCF} = \sum \frac{FCFE_{i,t}}{\left(1 + r_{E,i)}\right)^t} + \frac{TV_i}{\left(1 + r_{E,i}\right)^T}$$

For each firm i, FCFE is approximated using analyst forecast data from I/B/E/S, which provide expected cash flows per share (CPS). The CPS variable incorporates net income, depreciation and changes in working capital. To obtain firm-level values, CPS forecasts are multiplied by the number of shares outstanding, and dividends per share are subtracted to reflect shareholder distributions. Capital expenditures (CAPEX) are then deducted to derive an estimate of free cash flow to equity.

The general theoretical definition of FCFE is:

$$FCFE_i = Net\ Income_i + Depreciation_i - Capital\ Expenditures_i - \Delta Working\ Capital_i + Net\ Borrowing_i$$

Ideally, FCFE should incorporate the Net Borrowing component because equity holders ultimately receive cash flows net of changes in leverage. However, explicit information on new debt issuance and repayment is not available in the dataset used in this thesis and the net borrowing component cannot be measured directly. For this reason, it is assumed to be zero, which implies that firms

finance investments entirely through internal cash flows rather than through changes in leverage. While this simplification is necessary for methodological consistency across all firms, it may bias FCFE estimates for companies that rely heavily on debt financing. As a result, this limitation represents a structural source of noise in DCF valuations.

Each cash flow is discounted at the cost of equity, which is estimated through the CAPM:

$$r_{E,i} = r_f + \beta_i(r_M - r_f)$$

where r_f is the risk-free rate of return, β_i is the firm's systematic risk (estimated from CRSP data) and $(r_M - r_f)$ is the equity risk premium.

The terminal value (TV) is computed using the Gordon growth formula:

$$TV_i = \frac{FCFE_{i,T}(1+g)}{r_{E,i} - g}$$

To prevent unrealistic outcomes, the terminal value is set to zero when $FCFE_{i,T} < 0$ or when $g \geq r_{E,i}$.

The total equity value is thus:

$$Value_i^{DCF} = \sum \frac{FCFE_{i,t}}{(1 + r_{E,i})^t} + \frac{FCFE_{i,3}(1+g)}{(r_{E,i} - g)(1 + r_{E,i})^3}$$

4.2.2 Residual Income Model (RIM)

The Residual Income Model expresses equity value as the current book value of the company plus the present value of future residual (abnormal) earnings, which represent profits that exceed the required return on book equity.

$$Value_{i,t}^{RIM} = BV_i + \sum \frac{RI_{i,t}}{(1 + r_{E,i})^t} + \frac{TV_i}{(1 + r_{E,i})^T}$$

where BV_i is the current book value of equity and RI_t is the Residual Income for each time period, equivalent to:

$$RI_{i,t} = NI_{i,t} - r_{E,i}BV_{i,t-1}$$

Book value of equity evolves according to:

$$BV_{i,t} = BV_{i,t-1} + NI_{i,t} - DIV_{i,t}$$

ensuring consistence between earnings and dividends, where NI is the Net Income and DIV the dividends paid.

The terminal value (TV) is computed using the Gordon growth formula:

$$TV_i = \frac{RI_{i,T}(1+g)}{r_{E,i} - g}$$

If the residual income in the terminal year is negative or $g \geq r_{E,I}$, the terminal value is set to zero.

The total equity is thus:

$$Value_i^{RIM} = \sum \frac{RI_{i,t}}{\left(1 + r_{E,i)}\right)^t} + \frac{RI_{i,3}(1+g)}{\left(r_{E,i} - g\right)\left(1 + r_{E,i}\right)^3}$$

4.2.3 Net Asset Value (NAV)

The Net Asset Value model (NAV) values equity as the difference between a firm's total assets and total liabilities. It is a balance-sheet based approach to valuation, where the value of a company is set based on its recorded net worth rather than by its earnings or cash flow potential.

$$Value_i^{NAV} = Total\ Assets_i - Total\ Liabilities_i$$

This measure captures the book value of shareholders' equity and is especially relevant for firms whose assets can be reliably valued at or close to market value. Some examples of such companies are those that belong to the real estate, utility or financial companies. The NAV model approximates the liquidation value in these sectors and can serve as a lower bound for intrinsic value. However, NAV tends to underestimate the value of firms with substantial assets or growth opportunities, since it does not capitalize earnings potential or goodwill (Fernández, 2007). In the real world, book assets often diverge from market values due to accounting practices, depreciation policies, or other reasons.

Even though this method is much simpler than the others, NAV remains an important valuation benchmark in empirical research and professional practice, because it provides a tangible reference point against which more forward-looking models can be assessed in terms of their performance.

4.2.4 Multiples

The multiples valuation approach relies on the idea that companies that have similar fundamentals should also share similar valuation ratios. It is a market-based method that captures the expectations, risk perceptions and growth prospects that are implied in observed trading prices.

For the purposes of this thesis, the multiple that is used as a benchmark is the enterprise value to EBITDA ratio (EV/EBITDA), since it is one of the most widely used and empirically robust valuation ratios.

$$EV_i^{MULTIPLE} = \left({}^{EV}/_{EBITDA}\right)_j \times EBITDA_i$$

where $(EV/EBITDA)_j$ is the median multiple for an industry j (estimated through the Damodaran database) and $EBITDA_i$ are the earnings before interest, taxes, depreciation and amortization for a firm i.

To get the equity value of each company from the enterprise value, so that the results can be compared with those of the other valuation methods, it is important to adjust for net debt:

$$Value_i^{Multiple} = EV^{MULTIPLE}{}_i - Total\ Debt_i + Cash_i$$

Each firm in the sample is mapped to a Damodaran industry classification, based on the SIC codes provided from the Compustat Database. This ensures that the applied multiple reflects the valuation environment of the most relevant peer group.

The multiples method shows the best results when it is applied on firms that belong to an industry that shares comparable operating models and capital structures, such as manufacturing and utilities. In other words, to homogeneous sectors. However, in industries where capital structures and operating models can vary significantly for each company, the results are less encouraging and larger deviations can occur.

4.3 Accuracy Measurement

Once all four methods have been applied and the equity values for each company have been obtained, it is time to evaluate how closely these estimates correspond to observed market valuations. For each firm i and valuation method M, the absolute percentage deviation from the actual market capitalization P is calculated as:

$$\left|Error_{i,M}\right| = \left|\frac{Value_i^M - P_i}{P_i}\right| \times 100$$

This firm-level error represents the proportional deviation between theoretical and observed values and is the basis for all the accuracy statistics that follow. Two indicators are used to summarize the model accuracy: Mean Absolute Percentage Error (MAPE) and Median Absolute Percentage Error (MdAPE).

1. *Mean Absolute Percentage Error (MAPE):*

$$MAPE_M = \frac{1}{N}\sum_{t=1}^{N}\left|Error_{i,M}\right|$$

2. *Median Absolute Percentage Error (MdAPE):*

$$MdAPE_M = Median\left(\left|Error_{i,M}\right|\right)$$

Even though both indicators are reported for each of the four valuation models, MdAPE is the one this thesis mainly focuses on, as it provides a more robust measure of typical valuation performance in the presence of skewed error distributions. The interpretation of both indicators is quite simple: lower percentage values show greater precision and higher correspondence between model-based (theoretical) and market-observed (practical) valuations, while higher percentages show greater deviations and lower accuracy.

Accuracy is first evaluated at the aggregate level to compare the overall performance of the four valuation methods across the entire sample. Next, industry-level analyses are conducted whether accuracy differs systematically across different industries (Broad Industry categories, as shown in Table 3). This two-step approach enables both the general comparison of model performance and an assessment of sector-specific patterns in valuation accuracy.

4.4 Statistical Testing of pricing errors

In addition to the descriptive accuracy measures discussed above, statistical tests are applied to the firm-level absolute percentage errors to assess if the pricing deviations are statistically significant and whether valuation models differ in predictive performance. The pricing errors are non-negative and highly skewed, which means they are following a non-normal distribution, so standard parametric tests can produce misleading significance results (Dittman & Maug, 2008).

For this reason, the Wilcoxon signed-rank test is employed. It is a non-parametric test that evaluates whether the median pricing error differs from zero without relying on distributional assumptions and it reduces the influence of extreme observations by working with ranks rather than raw magnitudes. As a distribution-free procedure, it does not assume normality and is therefore well suited for the empirical characteristics of pricing errors.

First, for each valuation method, a one-sample Wilcoxon signed-rank test is used to test whether the MdAPE differs from zero. This establishes whether the valuation errors are statistically different from zero, rather than being attributable to random variation. Then, pairwise Wilcoxon signed-rank tests are conducted on the paired errors of alternative models, exploiting the fact that each firm is valued by all methods. These tests evaluate whether one model systematically yields larger or smaller errors than another when applied to the same observations.

The same testing framework is used to compare standalone, fundamentals-based and hybrid valuation approaches. For the fundamentals-based and hybrid models, all tests are conducted on the out-of-sample subsample to avoid overstating performance due to in-sample fitting. This combination of one-sample and paired comparisons provides a clear and robust statistical assessment of whether the observed differences in MAPE and MdAPE across valuation models are statistically meaningful.

4.5 Fundamentals-based valuation model

While the traditional valuation models generate firm-specific intrinsic values based on projected cash flows, accounting numbers or relative pricing benchmarks, they do not explicitly test whether valuation levels observed in the market can be systematically explained by firms' underlying financial fundamentals. Introducing a fundamentals-based model therefore serves two complementary purposes. First, it provides an economically grounded benchmark for understanding how markets capitalize financial information into valuation multiples. Second, it functions as an additional valuation method that can be evaluated using the same accuracy metrics as the traditional models, allowing its predictive performance to be compared with DCF, RIM, NAV and Multiples.

The decision to model the market-to-book (M/B) ratio rather than raw equity values is motivated by both statistical and economic considerations. From a statistical perspective, market capitalization is a non-stationary level variable that is strongly correlated with firm size, which can

lead to distorted coefficients and spurious relationships in cross-sectional regressions. The M/B ratio normalizes market value by book equity, creating a scale-free measure that is more suitable for identifying valuation patterns. Taking the natural logarithm of the M/B ratio further stabilizes variance and produces a distribution close to normality, thus improving the reliability of the regression estimates. Economically, the M/B ratio is a standard valuation metric used in both academic research and practice to capture how markets price current assets, growth opportunities and firm quality relative to book equity.

The explanatory variables are profitability (ROA), leverage, systematic risk (beta), expected growth and firm size (natural logarithm of total assets). Together, these variables represent the core financial characteristics that theory and prior empirical studies identify as key determinants of firm valuation. Profitability and expected growth capture firms' earning potential and future prospects, while leverage and beta reflect their financial and systematic risk. Firm size controls for differences in scale and maturity that may influence valuation levels.

To control for the unobserved heterogeneity across sectors, like different business models, risk exposure and capital intensity, industry fixed effects are also included. That way, the influence of firm-specific characteristics is isolated while accounting for industry-level patterns.

The regression model is the following:

$$\ln(M/B_i) = \alpha + \beta_1 ROA + \beta_2 Leverage_i + \beta_3 Beta_i + \beta_4 Growth_i + \beta_5 \ln(Total\ Assets_i) + Industry\ FE + \varepsilon_i$$

where $\ln(M/B_i)$ is the natural logarithm of a firm's i market-to-book ratio, ROA_i shows the companies' profitability, $Leverage_i$ represents capital structure, $Beta_i$ captures systematic risk, $Growth_i$ reflects the expected sales growth of companies and $\ln(\text{Total Assets}_i)$ measures firm size.

By estimating this regression, several econometric dangers occur that require special precautions to be applied. First, because of the big variation in firm sizes and revenues, some extreme observations are expected that could potentially distort the regression coefficients. To reduce the influence of these observations, continuous variables are winsorized at the 1st and 99th percentile. Heteroscedasticity is also expected, since larger firm tend to show greater variance in their market value. Therefore, robust standard errors are used to correct for non-constant variance in the residuals, which are also clustered by the broad industry category, to further account for potential

correlation of errors within sectors. Lastly, to test for any potential multicollinearity in the regression, variance-inflation factors are used.

Predicted log(M/B) ratios are exponentiated and multiplied by firms' book equity to obtain model-implied market capitalizations. To assess the model's predictive performance, the dataset is randomly divided into an 80% training subsample used for estimation and a 20% test subsample used for validation. The predicted values from each set are compared to actual market capitalizations to evaluate valuation accuracy using in-sample and out-of-sample mean and median absolute percentage errors (MAPE and MdAPE).

This fundamentals-based regression model serves as an additional valuation method and complements the traditional models, as well as the hybrid approaches that follow. It evaluates whether firm fundamentals alone can explain cross-sectional differences in market valuation with comparable accuracy.

4.6 Combination of Methods

The last part of this thesis examined whether the combination of the different valuation methods used earlier can provide better and more accurate results than each standalone model. The main idea is that each model captures different dimensions of the equity value of a firm (DCF focuses on discounted cash flows, RIM on accounting profitability, NAV on the balance sheet position and Multiples on market comparables) and by integrating complementary perspectives into one framework the model-specific errors can be averaged out and the overall predictive accuracy can be improved. However, despite the conceptual differences these models have, they all rely on largely overlapping accounting information and similar cost of capital assumptions. For that reason, their errors are often correlated and large improvements in accuracy are not expected. Even so, an increase in accuracy would still indicate that integrating these complementary valuation perspectives can reduce model-specific noise and yield more stable equity value estimates.

Three alternative versions of this hybrid model are estimated to test this hypothesis.

The first version assumes that all four valuation techniques are contributing equally to the overall assessment of the equity value, and therefore the weights assigned to each method are equal as well. This is the simplest method applied and is used mostly as a benchmark against which more sophisticated weighting schemes can be evaluated.

The model is the following:

$$Value_i^{HYB-EQ} = 0.25 \times Value_i^{DCF} + 0.25 \times Value_i^{RIM} + 0.25 \times Value_i^{NAV} + 0.25 \times Value_i^{Mult}$$

The second version assigns greater weight to the models that showed the highest accuracy in the training sample. The weights are determined by the inverse of each model's Mean Absolute Percentage Error (MAPE), so that the more accurate models will receive proportionally higher importance.

$$Value_i^{HYB-ACC} = w^{DCF} \times Value_i^{DCF} + w^{RIM} \times Value_i^{RIM} + w^{NAV} \times Value_i^{NAV} + w^{Mult} \times Value_i^{Mult}$$

Finally, the third version of the hybrid model introduces a dynamic weighting scheme that allows the contribution of each valuation method to vary across firms. Instead of using fixed weights for all observations, this approach assigns weights that depend on the firm's financial characteristics. The main idea is that valuation model performance is not uniform, since certain models perform better for specific types of firms (for example, DCF is more reliable for large and stable companies with predictable cash flows, while NAV may perform better in asset-heavy industries).

To capture these differences, the firm-level absolute percentage errors of each valuation model are first regressed on the main firm-specific variables identified earlier (profitability, leverage, beta, expected growth and size) together with industry fixed effects. These regressions estimate in which types of firms each valuation method achieves higher or lower accuracy. The predicted errors from these models are then transformed into positive, normalized weights using an exponential function, so that methods expected to have lower errors for a given firm receive proportionally higher weights.

$$Value_i^{HYB-DYN} = w_i^{DCF} \times Value_i^{DCF} + w_i^{RIM} \times Value_i^{RIM} + w_i^{NAV} \times Value_i^{NAV} + w_i^{Mult} \times Value_i^{Mult}$$

To evaluate the accuracy of these hybrid approaches, the sample is randomly divided into a 20% training subsample and a 20% test subsample. The training subsample is used to estimate the weights for the accuracy weighted and dynamically weighted models, while the test subsample is reserved for out-of-sample validation. This procedure ensures that the predictive accuracy of each model is assessed on data that were not used for parameter estimation, preventing overfitting. The equal weighted hybrid model, which does not involve parameter estimation, is evaluated on the full sample.

5. Results

5.1 Valuation accuracy across models

This section evaluates how closely each valuation approach reproduces observed market values. For each firm in the sample, the equity value calculated by each method is compared to the actual firm's market value. The accuracy of each method is determined by using the Mean Absolute Percentage Error (MAPE) and the Median Absolute Percentage Error (MdAPE), as explained in the methodology chapter. The lower the value of these metrics, the higher the accuracy of the valuation model.

Table 4 reports the MAPE and MdAPE for the four valuation models (DCF, RIM, NAV, Multiples) when they are applied across the whole market.

Table 4. Valuation accuracy across models (full sample)

Valuation Model	N.Obs	MAPE (%)	MdAPE (%)
DCF	494	70.24	47.44
RIM	494	68.25	42.79
NAV	494	73.43	58.88
Multiples	494	88.63	42.97

Starting with the DCF model, it produces a MAPE of 70.24% and a MdAPE of 47.44%. This means that on average, DCF valuations in the sample deviate from market prices by about 70% and that a typical (or median) firm is generally mispriced by about 47%. These values confirm that while DCF is a very well-known valuation method that is used a lot in practice, it still deviates substantially from the actual market values of the companies. The most important reason why this is happening is a structural characteristic of the method: it relies heavily on multi-year cash flow forecasts and on a terminal value component, both of which amplify small differences in assumptions about growth and discount rates.

The RIM model shows more promising results. It yields a MAPE of 68.25% and a MdAPE of 42.79%. Both metrics are below those of DCF. This outcome supports prior research suggesting that by grounding valuation in current book equity and short-term profitability, the RIM model

reduces the exposure to errors created from long-term forecasting and growth assumptions (Penman & Sougiannis, 1998; Francis et al., 2000). Overall, this indicates that RIM's accounting-based structure, which relies on book value of equity and realized earnings, enables it to capture firm value in a more consistent and economically grounded way.

NAV is the valuation method with the weakest accuracy in this research. It generates a MAPE of 73.43% and a MdAPE of 58.88%, which are the second highest and the highest among all valuation methods respectively when applied to the full sample. This result was expected and is consistent with the mechanical nature of NAV. Since it treats firm value primarily as an adjusted balance sheet position, it cannot capitalize future profitability or growth opportunities. Because of that, it systematically undervalues firms whose value is driven by intangible assets or other non-recorded drivers of value.

Lastly, the Multiples approach shows mixed results. While it delivers a MAPE of 88.63%, which is the highest by far across all models and indicates very weak accuracy capabilities, its MdAPE is equal to 42.97%, which is comparable to RIM and surprisingly lower that DCF. This indicates that while the comparables approach produces very large errors for some firms (which explain the high MAPE), its median error is quite competitive. In other words, Multiples can be a very useful valuation method for firms that have a capital structure and other operating characteristics that resembles those of their peers, but it can also produce very poor results for firms that differ from the industry benchmark due to factors such as leverage or other extraordinary events.

Summing up, the results are in line with the expectations from prior research. Other studies generally find that the residual income model tends to outperform pure cash flow valuation methods when the forecast horizon is short and the accounting data are reliable, while traditional balance sheet methods like NAV can only work in specific cases. (Francis et.al, 2000; Fernández, 2007).

Although the four standalone valuation methods produce broadly consistent rankings, their overall predictive accuracy is weak. The MdAPE of the models ranges from 43% to 59%, which indicates substantial deviations from observed market capitalizations. These levels are higher than those reported in earlier empirical valuation studies, suggesting that the traditional valuation methods struggle to capture firm-level valuation patterns within this dataset. The magnitude of the errors

highlights both the inherent noise in firm-level valuation and the limitations of relying on short-horizon analyst forecasts.

To determine whether these valuation errors are statistically meaningful, the firm-level absolute percentage errors for each method are evaluated using one-sample Wilcoxon signed-rank tests. The null hypothesis of zero median error is rejected for all four valuation models, with p-values effectively equal to zero (p-value $\approx 3.97 \times 10^{-82}$ for all models). This means that the pricing errors observed in the sample are highly significant and not the result of a random variation.

Pairwise Wilcoxon signed-rank tests further examine whether accuracy differs meaningfully across models. The RIM model produces significantly smaller errors than DCF (p-value = 0.0022), confirming its superior performance. NAV performs significantly worse than all three alternatives (p-values<0.01 in each comparison), which is consistent with its descriptive ranking. The Multiples model does not differ significantly from DCF (p-value = 0.296), but it does differ from RIM (p-value = 0.039). Overall, the statistical evidence supports the descriptive ranking, with RIM being the most accurate standalone approach, NAV being the least accurate, and DCF and Multiples offer intermediate performance depending on firm characteristics.

5.2 Industry-level accuracy differences

What is also interesting to test is whether these accuracy patterns are uniform across industries sector characteristics. For this reason, each of the four valuation methods is now applied separately to each of the 10 broad categories specified in the data section (Technology, Media & Telecom, Healthcare, Industrials, Consumer, Energy & Utilities, Basic Materials, Financials, Food & Beverages, Hotels, Leisure & Gaming and Environmental & Agriculture).

Table 5 reports the MdAPE for the four valuation models (DCF, RIM, NAV, Multiples) when they are applied across industries:

Table 5. Median absolute percentage error (MdAPE) by broad industry category and valuation model

Broad Category	Number of Firms	DCF	RIM	NAV	Multiples
Technology, Media & Telecom	103	57.49	53.86	74.21	51.81
Healthcare	82	46.08	51.8	60.51	58.55
Industrials	82	51.02	44.61	52.46	27.03
Consumer Goods	70	42.86	36.92	68.36	52.39
Energy & Utilities	52	35.62	21.6	32.9	38.5
Basic Materials	42	50.93	41.97	51.12	50.98
Financials	28	46.19	37.41	47.05	72.07
Food & Beverages	17	43.35	37.66	56.83	22.51
Hotels, Leisure & Gaming	11	48.83	49.65	70.55	42.19
Environmental & Agriculture	7	53.84	40.51	47.29	20.58

It is evident that when the accuracy of the valuation methods is examined at an industry level, no model performs best across all industries and each one exhibits distinct strengths depending on the underlying business structure and composition.

For the DCF model, its accuracy is significantly higher when applied to industries that are capital-intensive and cash-flow stable. The lowest MdAPE values appear in the Energy & Utilities (35.6%) and Food & Beverages (43.3%) sectors, both of which are characterized by predictable cash generation and relatively stable growth assumptions. On the contrary, it performs the worst in Technology, Media & Telecom (57,49%) and Environmental & Agriculture (53.84%), where earnings are more volatile and the terminal value assumptions are not as reliable as they should be. What is surprising is that the method is considered to be the most accurate in only one industry sector (Healthcare – 46.08%), which suggests that , despite being one of the most used valuation approaches in practice, in reality it is not as consistent as people tend to believe, and careful calibration of inputs and assumptions is necessary to avoid significant deviations from market valuations.

The RIM model again delivers more accurate results that the DCF In most sectors and is generally the most consistent across sectors. It performs particularly well in Energy & Utilities (21.6%), Food & Beverages (37.7%) and Financials (37.4%), reflecting the advantages of its accounting-based formulations. This relative stability across industries underscores its robustness as a valuation approach grounded in financial statements.

The NAV method remains the weakest one of the four, performing the worst in almost every industry sector. Even in industries where tangible assets are dominant, such as Energy & Utilities (32.9%) or Financials (47.1%), it is not as accurate as the result of other methods, even though it performs quite well. In industry sectors where intangible capital, brand value and growth potential exist, such as Technology, Media & Telecom (74.2%) and Hotels, Leisure & Gaming (70.6%), the performance is NAV is significantly inferior to the other models. These findings confirm that NAV provides at best a rough lower bound for firm value and is most applicable in asset-heavy environments.

Out of the four models, Multiples displays the most unexpected results. It produces very high accuracy in Industrials (27.0%), Food & Beverages (22.5%) and Environmental & Agriculture (20.6%), where firms share a similar operating structure and is the best performing model there. In contrast, its accuracy declines sharply in Financials (72.1%) and Healthcare (58.6%), where the ability to compare with peers is quite limited. This supports the idea that the multiples approach can be very useful when it is applied to homogeneous industries with standardized business models, but it becomes very unreliable where the firm fundamentals diverge widely.

Overall, the cross-industry evidence indicates that there is no single best valuation method across all sectors. DCF is most effective for stable, asset-based sectors, while RIM tends to outperform it and demonstrate consistent accuracy across most industries. NAV is the weakest method and is only useful to be applied in a few asset-heavy industries. Finally, Multiples perform well in industries where comparables truly reflect firm fundamentals.

Hypotheses Evaluation (H1-H3)

The results presented above allow for the empirical evaluation of the first three hypotheses:

- H1: RIM outperforms DCF in terms of accuracy because it anchors valuations in book value and near-term earnings.

⇒ Supported. RIM consistently yield lower MdAPE values than DCF both when applied to the whole sample and across industries.

- H2: NAV performs better than other methods in asset-heavy sectors (e.g. financials, real estate), but performs much worse in intangible-intensive industries (e.g. technology)

⇒ Partially supported. NAV is more accurate in asset-heavy sectors, but it is still underperforming over the other models.

- H3: Multiples achieve competitive accuracy, but their performance depends critically on peer selection and industry homogeneity.

⇒ Supported. The Multiples method shows very promising results in homogenous sectors such as Industrials, Food & Beverages and Environmental & Agriculture.

5.3 Fundamentals-based valuation model

5.3.1 Model regression

After examining how accurate each valuation model is at capturing the real market value of companies, the next step is to explore which firm characteristics explain these valuation differences. By identifying which factors drive variation in market-to-book ratios, an economic context for the valuation outcomes presented earlier is provided.

As shown in the previous chapter, the regression used is the following: $\ln(M/B_i) = \alpha + \beta_1 ROA + \beta_2 Leverage_i + \beta_3 Beta_i + \beta_4 Growth_i + \beta_5 \ln(Total\ Assets_i) + Industry\ FE + \varepsilon_i$

Three different models were estimated using the same sample of firms. In model (I), only Firm Profitability is included. In model (II) the variables Leverage, Risk, Growth and Size are added, while in model (III) introduces industry fixed effects to control for sector-level heterogeneity. To ensure reliable inference, robust standard errors (HC1) are used in models (I) and (II) to correct for potential heteroskedasticity, while for model (III) the standard errors are clustered by industry, allowing for correlation of residuals within sectors.

Table 6 reports the regression outcomes:

Table 6: Determinants of Market Value

Dependent Variable: ln (Market-to-Book Ratio)	(I)	(II)	(III)
Profitability	6.565***	5.722 ***	5.672**
	(0.761)	(0.747)	(1.299)
Leverage		-1.645***	-1.666**
		(0.276)	(0.491)
Beta		-0.088	-0.069
		(0.081)	(0.099)
Expected Growth		1.352***	1.209*
		(0.377)	(0.529)
Size		0.001	0.019
		(0.031)	(0.053)
Observations	494	494	494
R^2 Adjusted	0.179	0.337	0.378
Industry FE	No	No	Yes
Std.Errors	HC1	HC1	Clustered By Industry

Notes: Dependent variable ln (Market-to-Book Ratio). Standard errors in parentheses. Models I & II use HC1 SE; Model III clusters SE clustered by industry.

Profitability seems to be the strongest determinant of market-to-book ratios. It is strongly significant and positively related to the dependent variable, meaning that the more profitable a company is, the higher its valuation will be relative to its book value. This relationship is consistent with valuation theory, according to which profitability reflects a company's ability to generate

returns above its cost of capital, thereby increasing its intrinsic value. A 1-percentage increase in profitability leads to a 5.7% rise in the market-to-book ratio, according to these regressions.

Leverage is consistently negative and significant in models (II) and (III). The size of the coefficients indicates that a 10-percentage point increase in leverage is associated with a 16% decrease in the market-to-book ratio. This effect reflects the penalizing role of financial risk: firms that rely more heavily on debt face higher required returns from investors, leading to lower equity valuations. This relationship is stable even when industry differences are taken into account.

Risk (Beta) is negatively correlated with the market-to-book ratio, indicating that as the systematic risk rises for a company, its market-to-book ratio will drop. However, that relationship is not statistically significant in model (II) and becomes even more insignificant when industry fixed effects are introduced in model (III). This indicates that systematic risk does not have a strong independent effect once other fundamentals are controlled for, and the fact that fixed effects make it even less significant suggests that much of the variation in systematic risk operates at the sector level rather than at the firm level.

Expected growth is statistically significant and positively correlated with the market-to-book ratio. Firms with stronger growth prospects are prices more highly relative to their book value, reflecting expectations of future earnings expansion. A 10-percentage point increase in expected growth raises the market-to-book ratio by approximately 12%.

Firm size does not exhibit a meaningful relationship with valuation multiples. The coefficients are close to zero and are not statistically significant across models. This suggests that's, after accounting for other fundamentals, differences in firm scale do not systematically affect market-to-book ratios.

Introducing the industry fixed effects in our model has slightly increased its overall explanatory power (R^2 Adjusted=0.378), meaning that part of the valuation ratios variation is industry specific. Once these sectoral patterns are accounted for, the coefficients for profitability, leverage and expected growth remain economically meaningful and retain their expected signs, though their statistical significance declines slightly. This suggests that part of the explanatory power of these variables is shared with broad industry characteristics, but the fact that they remain significant

even after controlling for fixed effects confirms that they continue to play an important role in explaining cross-sectional valuation differences.

Finally, a multicollinearity test was conducted using Variance Inflation Factors (VIFs) to ensure that the independent variables used are not inflating each other's variance. VIF quantifies the correlation between variables by indicating how much the variance of an estimated coefficient is inflated due to correlations with other regressors. A value of 1 suggests no correlation, while values above 5 (and especially above 10) are typically viewed as problematic. The results of the test are shown in the following table:

Table 7: Variance Inflation Factors (VIFs)

Variable	VIF.Value	Interpretation
Profitability	1.294	Low multicollinearity
Leverage	1.323	Low multicollinearity
Beta	1.103	Low multicollinearity
Growth	1.297	Low multicollinearity
Size	1.158	Low multicollinearity

Notes: VIF values below 5 indicate low multicollinearity; values above 10 suggest a potential concern.

By observing the results of the test, it is evident that there is no multicollinearity among the regressors used, since all of them are substantially below the conventional threshold value of 5.

5.3.2 Predictive accuracy of the Fundamentals-based model

The next step is to evaluate the predictive performance of the fundamentals-based model when used as a valuation tool. To do so, the estimated log(M/B) ratios are transformed into predicted market capitalizations by exponentiating the fitted values and multiplying them by firms' book equity. Then these valuations that are implied by the model are compared to actual market capitalizations using the Mean Absolute Percentage Error (MAPE) and the Median Absolute Percentage Error (MdAPE).

In order to assess both in and out of sample predictive validity, the dataset is split randomly into an 80% training subsample and a 20% test subsample. By doing so, it is ensured that the model's performance is not overstated by overfitting the data. Also, it allows for a more realistic

comparison with the traditional valuation techniques considered earlier. The results are shown in the table below:

Table 8. Valuation Accuracy across standalone vs fundamentals-based model

Model	MAPE (%)	MdAPE (%)
DCF	70.24	47.44
RIM	68.25	42.79
NAV	73.43	58.88
Multiples	88.63	42.97
Fundamentals-based model (in-sample)	63.61	45.86
Fundamentals-based model (out-of-sample)	60.33	50.94

The results indicate that the fundamentals-based model achieves an in-sample MAPE of 63.61% and a MdAPE of 45.86%, while the out-of-sample MAPE is 60.33% and the MdAPE is 50.94%. Even though the MAPE values are lower than those of the traditional valuation methods, which indicates that on average the fundamentals-based predictions deviate less from the market values, the same cannot be said for the MdAPE values. In fact, the MdAPE is higher for the new model than the standalone ones, both in-sample and especially out-of-sample. Since MdAPE is the preferred accuracy measure for this analysis, since it is more robust to extreme observations, this finding suggests that the fundamentals-based approach does not outperform the traditional models for the typical firm in the sample.

The lower MAPE combined with a higher MdAPE implies that the fundamentals-based model yields a small number of very accurate predictions, that bring down the mean error, while at the same time it generates many moderate to large errors, which raise the median. The accurate predictions belong to firms whose valuation aligns closely with the pricing patterns captured by profitability, leverage, long term growth and industry fixed effects. On the other hand, firms whose valuation drivers are not fully reflected in these fundamentals (for example intangible assets or unusual capital structures) tend to show larger deviations. This results in a good performance of the model for a subset of firms but a failure to improve the accuracy for most of the sample.

The out-of-sample MdAPE result, which is the relevant measure for assessing the predictive performance of the model, confirms this. It is worse than the MdAPE of any standalone valuation model except NAV, which indicates that once tested on unseen firms, the fundamentals-based model does not provide more accurate valuations than the traditional models. This is reinforced by using the Wilcoxon signed-rank procedures that were applied to the standalone methods. The one-sample Wilcoxon test confirms that its median absolute percentage error is significantly greater that zero (p-value = 3.97×10^{-82}), which is consistent with the results for DCF, RIM, NAV and Multiples. The pairwise Wilcoxon tests show that the model performs better than NAV ($p < 0.0001$), but its errors are not significantly different from those of the DCF, RIM and Multiples models. This result is consistent with the descriptive evidence in Table 8, where the fundamentals-based model delivers average errors that are competitive with the traditional methods but fails to improve on their typical firm-level performance.

In terms of overall explanatory and predictive power, this valuation approach exhibits limited power. Although the regression coefficients align with economic intuition, the pricing errors are of similar magnitude to the standalone valuation approaches, reinforcing the fact that even economically grounded cross-sectional relationships between market-to-book ratios, profitability, leverage, risk, growth and size only offer partial insight into firm-level valuation. These fundamentals capture broad patterns in market pricing, but they are not sufficiently rich to account for the full heterogeneity observed across firms.

To sum up, while this fundamentals-based valuation model achieves competitive average accuracy and offers a transparent and theoretically grounded benchmark, it does not provide meaningful improvements for the typical U.S. firm. Therefore, it does not outperform the traditional valuation models in terms of accuracy.

Hypothesis Evaluation (H4)

The regression outcomes provided above allow the empirical evaluation of hypothesis 4:

- H4: A fundamentals-based regression model predicting market-to-book ratios from firm characteristics provides valuation accuracy comparable to traditional valuation methods.

⇒ Not Supported. While its average errors are similar to those of the traditional models, the fundamentals-based approach produces larger typical valuation errors and weaker out-of-

sample performance, indicating that it does not match the accuracy of the established valuation methods.

5.4 Combination of Methods

Having examined the performance of the traditional valuation models and the fundamentals-based regression approach, the final step is to investigate whether combining multiple valuation methods can improve predictive accuracy.

As discussed in the previous chapter, the three versions of combination models are the following:

- Equally Weighted Model

$$Value_i^{HYB-EQ} = 0.25 \times Value_i^{DCF} + 0.25 \times Value_i^{RIM} + 0.25 \times Value_i^{NAV} + 0.25 \times Value_i^{Mult}$$

- Accuracy Weighted Model

$$Value_i^{HYB-ACC} = w^{DCF} \times Value_i^{DCF} + w^{RIM} \times Value_i^{RIM} + w^{NAV} \times Value_i^{NAV} + w^{Mult} \times Value_i^{Mult}$$

- Dynamically Weighted Model

$$Value_i^{HYB-DYN} = w_i^{DCF} \times Value_i^{DCF} + w_i^{RIM} \times Value_i^{RIM} + w_i^{NAV} \times Value_i^{NAV} + w_i^{Mult} \times Value_i^{Mult}$$

After the computations are completed, the weights assigned to the accuracy weighted model are shown below:

$$Value_i^{HYB-ACC} = 0.264 \times Value_i^{DCF} + 0.272 \times Value_i^{RIM} + 0.254 \times Value_i^{NAV} + 0.210 \times Value_i^{Mult}$$

The accuracy weighted and the dynamically weighted hybrid models are evaluated using the same 80% training / 20% test split that was used in the fundamentals-based model to ensure a fair assessment. The training subsample is used to determine weights, and the test subsample is reserved for out-of-sample evaluation. The equal-weighted model does not require parameter estimation and for that reason it is evaluated on the full sample.

Table 9 reports the accuracy of the three hybrid models alongside the standalone methods and the fundamentals-based model, measured by both MAPE and MdAPE.

Table 9. Valuation Accuracy: standalone vs fundamentals-based vs hybrid models.

Model	MAPE (%)	MdAPE (%)
DCF	70.24	47.44
RIM	68.25	42.79
NAV	73.43	58.88
Multiples	88.63	42.97
Fundamentals-based model (in-sample)	63.61	45.86
Fundamentals-based model (out-of-sample)	60.33	50.94
Hybrid-Equally Weighted	63.11	40.34
Hybrid-Accuracy Weighted (in-sample)	61.35	39.17
Hybrid-Accuracy Weighted (out-of-sample)	61.37	43.18
Hybrid-Dynamically Weighted (in-sample)	50.64	39.02
Hybrid-Dynamically Weighted (out-of-sample)	71.80	41.21

The results show that the hybrid valuation approaches generally outperform the standalone methods and the fundamental-based model in terms of predictive accuracy, but only slightly and it depends on whether accuracy is evaluated in-sample or out-of-sample. The equal weighted hybrid model has a MAPE of 63.11% and a MdAPE of 40.34%, improving upon the DCF and RIM benchmarks by roughly 10 percentage points. This suggests that even a simple averaging of model outputs can smooth out idiosyncratic model errors and yield more stable valuation estimates.

The accuracy weighted hybrid model shows a slightly better accuracy in-sample, with a MAPE of 61.35% and a MdAPE of 39.17%. The improvement is modest but consistent, which shows that the fit to observed market values is enhanced when the model weighting is based on their past accuracy. However, the estimated weights of this method are relatively close to equal, ranging from 0.21 to 0.27, indicating that no valuation method dominates the others in explanatory power. More importantly, the out-of-sample performance deteriorates, with a MAPE of 61.37% and a MdAPE of 43.18%, achieving an accuracy comparable to that of the best performing standalone

approaches. This indicates that the accuracy weighting scheme may overfit the training data and does not generalize as effectively to unseen firms.

The dynamically weighted hybrid model achieves the strongest improvement among all contributions in-sample. Its MAPE equals 50.64%, representing a significant reduction relative to the equally weighted and accuracy weighted models, while its MdAPE is 39.02%, broadly comparable to the other hybrids. This means that although the median firm experiences a similar level of valuation error, the overall distribution of errors is considerably narrower, and large deviations are reduced significantly. However, its out-of-sample accuracy is significantly lower with a MAPE of 71.80%, which is the highest observed value of any hybrid model, and a MdAPE of 41.21%, which is comparable to the other hybrids and slightly better than the standalone models. This divergence between in-sample and out-of-sample accuracy shows that the flexibility of the dynamic approach comes at the cost of stability and predictive robustness.

To assess whether the improvements delivered by the hybrid models are statistically meaningful, their out-of-sample absolute percentage errors are compared to those of the strongest standalone models using paired Wilcoxon signed-rank tests. None of the hybrid approaches significantly outperform the RIM model in the test subsample, with p-values between 0.489 and 0.517. This means that although the hybrid models reduce valuation noise relative to several standalone approaches, they do not surpass the robust performance of the RIM model in out-of-sample prediction.

In contrast, all hybrid versions produce significantly smaller errors than the Multiples method in the out-of-sample test set, with p-values ranging from 0.0098 to 0.0134. Overall, the evidence indicates that hybrid valuation frameworks enhance accuracy relative to the weaker standalone models but do not deliver statistically significant improvements over the strongest individual benchmark.

Hypothesis Evaluation (H5)

Based on these results, the evaluation of hypothesis 5 is possible:

- H5: Combining traditional valuation methods into a hybrid valuation model achieves higher accuracy than the individual standalone methods.

⇒ Partially supported. Ther equal weighted and the dynamically weighted hybrid models achieve higher accuracy capabilities in terms of MdAPE. However, the accuracy-based hybrid does not consistently outperform the traditional models, particularly out-of-sample. Moreover, the dynamically weighted model exhibits a higher out-of-sample MAPE, signaling weaker overall predictive reliability.

6. Conclusion

This thesis examined the accuracy of the main firm valuation models and assessed whether combining them into hybrid frameworks can improve predictive performance. Using a dataset of 494 U.S. listed companies that integrates financial, market and forecast information from Compustat, CRSP, I/B/E/S and Damodaran, the analysis compared four widely used valuation approaches (DCF, RIM, NAV and Multiples) and evaluated their ability to reproduce observed market valuations. The study also estimated a fundamentals-based valuation model, relating market-to-book ratios to firm-specific characteristics to provide an additional benchmark for understanding how well accounting and financial fundamentals explain market value. Finally, the thesis tested if the combination of the four traditional approaches into hybrid valuation models can yield more stable and accurate valuation outcomes.

The results reveal that all valuation methods produce substantial deviations from market values. Median absolute percentage errors range from approximately 43 percent to 59 percent across the four standalone models, indicating that traditional valuation techniques struggle to capture firm-level valuation patterns within this sample. Among the standalone approaches, the RIM model delivers the most consistent performance and significantly outperforms the DCF method, while NAV performs the weakest overall. Multiples exhibit large mean errors but deliver relatively competitive median accuracy, particularly in more homogeneous sectors. These findings highlight the inherent limitations of relying on short-horizon forecasts, accounting-based adjustments or industry comparables when valuing individual firms.

The fundamentals-based valuation model offers additional insights into the drivers of market valuations. While the estimated coefficients align with economic expectations, indicating that firm profitability and expected growth positively influence value, while leverage has a negative effect, the model's predictive accuracy remains modest. In-sample errors are competitive with the standalone methods, but out-of-sample accuracy deteriorates, suggesting that firm fundamentals explain only part of the cross-sectional variation in market values. This reflects the challenges of capturing forward-looking market expectations using accounting and financial data alone.

The hybrid valuation models demonstrate that combining multiple approaches can mitigate some of the weaknesses of individual methods. The equal-weighted and accuracy-weighted hybrids achieve lower median errors than most standalone models, particularly relative to NAV and

Multiples. The dynamically weighted hybrid performs strongly in-sample but exhibits signs of overfitting, with substantially weaker accuracy out-of-sample. These results indicate that hybrid frameworks can reduce model-specific noise and improve stability, but they do not dominate the strongest individual model.

Overall, this thesis shows that widely used valuation models exhibit substantial and statistically significant errors when applied at the firm level. Although hybrid approaches enhance accuracy relative to weaker standalone methods, the improvements remain modest and do not eliminate the core challenges of firm valuation. Future research could examine whether alternative forecasting horizons, additional information sources or more flexible machine learning-based weighting schemes can further improve robustness. Examining performance across different market environments or applying the analysis to non-US markets may also provide deeper insights into when and why particular valuation models succeed or fail.

7. References

Bhojraj, Sanjeev, and Charles MC Lee. "Who is my peer? A valuation-based approach to the selection of comparable firms." *Journal of accounting research* 40.2 (2002): 407-439.Comblain, A. (2021). *Common valuation errors in corporate finance practice: Evidence from small firms* [Unpublished manuscript].

Damodaran, A. (2024). *Annual data: Cost of capital, risk premiums, and industry averages* [Data set]. Stern School of Business, New York University.

Damodaran, Aswath. *Investment valuation: Tools and techniques for determining the value of any asset*. John Wiley & Sons, 2012.

Dittmann, Ingolf, and Ernst G. Maug. "Biases and error measures: How to compare valuation methods." *ERIM Report Series Reference No. ERS-2006-011-F&A, Mannheim Finance Working Paper* 2006-07 (2008).

Dittmann, Paweł. "The cost of forecast errors in company sales forecast." *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu. Ekonometria* 28.91 Prognozowanie= Forecasting (2010): 35-42.

Fernández, Pablo. "Company valuation methods. The most common errors in valuations." *IESE Business School* 449 (2007): 1-27.

Fernandez, Pablo, Javier Aguirreamalloa, and Luis Corres Avendaño. "Market risk premium used in 56 countries in 2011: a survey with 6,014 answers." (2011).

Francis, Jennifer, Per Olsson, and Dennis R. Oswald. "Comparing the accuracy and explainability of dividend, free cash flow, and abnormal earnings equity value estimates." *Journal of accounting research* 38.1 (2000): 45-70.

Gao, Zhan, et al. "Can a hybrid method improve equity valuation? An empirical evaluation of the Ohlson and Johannesson (2016) model." *The Accounting Review* 94.6 (2019): 227-252.

Grandis, Fabio Giulio, and Federica Palazzi. "The valuation of small and medium-sized enterprises." *Piccola Impresa/Small Business* 2 (2015).

Kaplan, Steven N., and Richard S. Ruback. "The valuation of cash flow forecasts: An empirical analysis." *The journal of Finance* 50.4 (1995): 1059-1093.

Klunder, R. (2016). *Determinants of valuation accuracy in SME transactions: Evidence from the Netherlands* [Master's thesis, Tilburg University]. Tilburg University Repository.

Lie, Erik, and Heidi J. Lie. "Multiples used to estimate corporate value." *Financial Analysts Journal* 58.2 (2002): 44-54.

Penman, Stephen H., and Theodore Sougiannis. "A comparison of dividend, cash flow, and earnings approaches to equity valuation." *Contemporary accounting research* 15.3 (1998): 343-383.

Penman, Stephen H., and Stephen H. Penman. *Financial statement analysis and security valuation*. New York: McGraw-Hill/Irwin, 2010.

Rodríguez-Valencia, Leslie, Prosper Lamothe-Fernández, and David Alaminos. "The market value of SMEs: a comparative study between private and listed firms in alternative stock markets." *Annals of Finance* 19.1 (2023): 95-117.

Trugman, Gary R. *Understanding business valuation: A practical guide to valuing small to medium sized businesses*. John Wiley & Sons, 2016.

Vallejo-Alonso, Belén, José Domingo García-Merino, and Gerardo Arregui-Ayastuy. "Motives for financial valuation of intangibles and business performance in SMEs." *Innovar* 25.56 (2015): 113-128.

8. Appendix

Table 1: Descriptive Statistics — Valuation Inputs (Compustat & CRSP)

Variables	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
Beta	494	1.20	0.49	0.44	1.14	2.10
Book Equity (USD mn)	494	11219.08	28127.86	416.83	3622.15	41131.70
Capital Expenditures (USD mn)	494	1329.06	5306.84	10.12	262.24	4449.55
Cash & Equivalents (USD mn)	494	2811.85	8362.34	55.36	762.67	10906.52
Change in Working Capital (USD mn)	494	-79.63	1938.16	-2098.40	-3.78	1861.36
Depreciation (USD mn)	494	1129.96	2877.55	24.32	334.50	4034.65
EBITDA (USD mn)	494	3973.21	10321.36	51.65	1189.85	14587.00
Employees	494	32	82	1	13	111
Enterprise Value (USD mn)	494	55597.33	157419.27	1674.69	15521.44	199182.08
Interest Expense (USD mn)	494	398.95	861.57	1.31	156.04	1447.00
Market Capitalization (USD mn)	494	49048.62	154137.84	1220.45	12357.91	170722.35
Net Debt (USD mn)	494	6548.71	16845.05	-1595.12	2173.64	29802.91
Net Income (USD mn)	494	1858.45	6616.95	-453.67	489.39	6628.70
Operating Income after Depreciation (USD mn)	494	2843.24	7899.29	-21.59	822.00	10158.65
Sales (USD mn)	494	20217.98	51233.89	685.40	6345.80	81015.20
Share Price (USD)	494	123.72	145.68	9.84	73.94	418.75
Shares Outstanding (mn)	494	466.98	1010.88	40.19	189.58	1705.01
Total Assets (USD mn)	494	29878.80	61766.49	1237.63	9902.10	118843.40
Total Debt (USD mn)	494	9360.56	19706.66	66.76	3181.00	35435.92
Total Liabilities (USD mn)	494	18259.41	37526.31	487.93	5702.40	77170.85
WACC	494	0.09	0.02	0.06	0.09	0.12

Note: The table reports descriptive statistics for the final sample (N = 494). All monetary variables are in millions of USD. Variables include only Compustat and CRSP inputs used in the valuation models (DCF, RIM, NAV, Multiples). WACC is constructed from firm accounts and market inputs; the risk-free rate and equity risk premium are constant across firms.

Table 2: Damodaran Industries — Sample Coverage and EV/EBITDA for 2024

Industry (Damodaran)	N Obs	EV/EBITDA
Advertising	4	12.94
Aerospace/Defense	11	18.49
Air Transport	3	6.17
Apparel	5	7.92
Auto & Truck	6	21.65
Auto Parts	7	7.06
Bank (Money Center)	0	-
Banks (Regional)	0	-
Beverage (Alcoholic)	4	14.84
Beverage (Soft)	3	18.07
Broadcasting	6	7.31
Brokerage & Investment Banking	5	-
Building Materials	3	12.01
Business & Consumer Services	9	16.12
Cable TV	2	7.8
Chemical (Basic)	5	8.1
Chemical (Diversified)	0	15.4
Chemical (Specialty)	14	12.85
Coal & Related Energy	0	2.75
Computer Services	44	12.61
Computers/Peripherals	3	21.83
Construction Supplies	3	11.12
Diversified	2	8.93
Drugs (Biotechnology)	13	13.52
Drugs (Pharmaceutical)	14	16.62
Education	2	10.8
Electrical Equipment	5	14.65
Electronics (Consumer & Office)	0	19.14
Electronics (General)	10	13.59
Engineering/Construction	3	12.76
Entertainment	4	16.37
Environmental & Waste Services	5	15
Farming/Agriculture	2	8.97
Financial Svcs. (Non-bank & Insurance)	8	62.48
Food Processing	8	12.51
Food Wholesalers	2	11.26
Furn/Home Furnishings	5	9.37
Green & Renewable Energy	0	12.63
Healthcare Products	21	21.51
Healthcare Support Services	15	11.29
Healthcare Information and Technology	15	21.44
Homebuilding	0	7.79

Industry (Damodaran)	N Obs	EV/EBITDA
Hospitals/Healthcare Facilities	4	8.75
Hotel/Gaming	11	14.98
Household Products	3	15.95
Information Services	0	12.15
Insurance (General)	6	11.48
Insurance (Life)	0	17.24
Insurance (Prop/Cas.)	0	11.77
Investments & Asset Management	2	34.85
Machinery	21	15.46
Metals & Mining	8	10.36
Office Equipment & Services	0	9.34
Oil/Gas (Integrated)	0	6.24
Oil/Gas (Production and Exploration)	21	4.67
Oil/Gas Distribution	5	7.31
Oilfield Svcs/Equip.	20	5.42
Packaging & Container	8	8.63
Paper/Forest Products	1	7.06
Power	6	11.69
Precious Metals	10	13.01
Publishing & Newspapers	1	10.52
R.E.I.T.	3	21.02
Real Estate (Development)	0	17.93
Real Estate (General/Diversified)	0	18.01
Real Estate (Operations & Services)	4	14.98
Recreation	3	9.99
Reinsurance	0	7.28
Restaurant/Dining	4	16.6
Retail (Automotive)	6	11.63
Retail (Building Supply)	2	13.33
Retail (Distributors)	7	11.63
Retail (General)	0	16.63
Retail (Grocery and Food)	2	6.38
Retail (REITs)	0	17.43
Retail (Special Lines)	6	9.34
Rubber& Tires	0	7.95
Semiconductor	9	31.59
Semiconductor Equip	3	18.18
Shipbuilding & Marine	3	8.38
Shoe	3	18.95
Software (Entertainment)	0	17.16
Software (Internet)	0	19.33
Software (System & Application)	13	28.43
Steel	4	5.93
Telecom (Wireless)	5	9.01

Industry (Damodaran)	N Obs	EV/EBITDA
Telecom. Equipment	2	13.98
Telecom. Services	1	6.18
Tobacco	0	10.84
Transportation	4	12.01
Transportation (Railroads)	3	14.32
Trucking	9	10.57
Utility (General)	0	11.7
Utility (Water)	0	16.86

Note: N Obs is the number of firms in the final sample mapped to each Damodaran industry. EV/EBITDA values are taken from the Damodaran multiples file.

Table 3: Broad Industry Categories for 2024

Broad Category	N.Obs
Technology, Media & Telecom	103
Healthcare	82
Industrials	82
Consumer Goods	70
Energy & Utilities	52
Basic Materials	42
Financials	28
Food & Beverages	17
Hotels, Leisure & Gaming	11
Environmental & Agriculture	7

Table 4. Valuation accuracy across models (full sample)

Valuation Model	N.Obs	MAPE (%)	MdAPE (%)
DCF	494	70.24	47.44
RIM	494	68.25	42.79
NAV	494	73.43	58.88
Multiples	494	88.63	42.97

Table 5. Median absolute percentage error (MdAPE) by broad industry category and valuation model

Broad Category	Number of Firms	DCF	RIM	NAV	Multiples
Technology, Media & Telecom	103	57.49	53.86	74.21	51.81
Healthcare	82	46.08	51.8	60.51	58.55
Industrials	82	51.02	44.61	52.46	27.03
Consumer Goods	70	42.86	36.92	68.36	52.39
Energy & Utilities	52	35.62	21.6	32.9	38.5
Basic Materials	42	50.93	41.97	51.12	50.98
Financials	28	46.19	37.41	47.05	72.07
Food & Beverages	17	43.35	37.66	56.83	22.51
Hotels, Leisure & Gaming	11	48.83	49.65	70.55	42.19
Environmental & Agriculture	7	53.84	40.51	47.29	20.58

Table 6: Determinants of Market Value

Dependent Variable: ln(Market-to-Book Ratio)	(I)	(II)	(III)
Profitability	6.565***	5.722 ***	5.672**
	(0.761)	(0.747)	(1.299)
Leverage		-1.645***	-1.666**
		(0.276)	(0.491)
Beta		-0.088	-0.069
		(0.081)	(0.099)
Expected Growth		1.352***	1.209*
		(0.377)	(0.529)
Size		0.001	0.019
		(0.031)	(0.053)
Observations	494	494	494
R^2 Adjusted	0.179	0.337	0.378
Industry FE	No	No	Yes
Std.Errors	HC1	HC1	Clustered By Industry

Notes: Dependent variable ln(Market-to-Book Ratio). Standard errors in parentheses. Models I & II use HC1 SE; Model III clusters SE clustered by industry.

Table 7: Variance Inflation Factors (VIFs)

Variable	VIF.Value	Interpretation
Profitability	1.294	Low multicollinearity
Leverage	1.323	Low multicollinearity
Beta	1.103	Low multicollinearity
Growth	1.297	Low multicollinearity
Size	1.158	Low multicollinearity

Notes: VIF values below 5 indicate low multicollinearity; values above 10 suggest a potential concern.

Table 8. Valuation Accuracy across standalone vs fundamentals-based model

Model	**MAPE (%)**	**MdAPE (%)**
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Hybrid-Equally Weighted	63.11	40.34
Hybrid-Accuracy Weighted (in-sample)	61.35	39.17
Hybrid-Accuracy Weighted (out-of-sample)	61.37	43.18
Hybrid-Dynamically Weighted (in-sample)	50.64	39.02
Hybrid-Dynamically Weighted (out-of-sample)	71.80	41.21

9. Acknowledgement of AI use

In line with the MSc Finance policy on the responsible use of AI tools, I acknowledge that I used AI assistance (ChatGPT by OpenAI) during the preparation of this thesis for supportive purposes only. The assistance was limited to:

1. Proofreading and language editing to enhance grammar, coherence and clarity.
2. Idea generation and phrasing refinement to improve sentence structure and flow.
3. Coding support for resolving syntax issues and troubleshooting R code.

No substantive content, analyses or results were generated by AI. All arguments, interpretations and conclusions presented in this thesis are entirely my own, and all references have been manually checked for accuracy.