

ARE THE INTRINSIC VALUE ESTIMATES OF THREE FLOW-BASED MODELS ANY LESS RELIABLE AS COMPARED TO THOSE OF A MULTIPLES-BASED MODEL?

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Abstract

This study examines the reliability of intrinsic value estimates generated by three flow-based valuation models, the Discounted Dividend Model (DDM), Discounted Cash Flow Model (DCF), and Residual Income Model (RIM), in comparison with multiples-based approaches such as Price-to-Earnings (P/E), Price-to-Book (P/B), and Enterprise Value to EBITDA (EV/EBITDA). Drawing on 195,845 firm-year observations from the S&P Compustat database, the analysis employs valuation error metrics including Mean Absolute Percentage Error, Root Mean Squared Error, and Median Absolute Deviation, along with paired t-tests and regression techniques to assess model accuracy and robustness.

Results indicate that flow-based models, particularly the DCF, exhibit substantially higher valuation errors and dispersion due to their sensitivity to assumptions regarding discount rates, growth trajectories, and terminal values. The DCF's mean absolute error exceeded that of multiples-based models, underscoring its lower reliability in aggregate settings. By contrast, the RIM, an accounting-anchored flow model, produced error levels comparable to multiples, suggesting greater robustness under certain conditions. Multiples-based models consistently delivered more stable and tightly clustered estimates, benefiting from reliance on observable market comparables and reduced dependence on forecasting assumptions.

Further analysis shows that firm-specific characteristics shape model performance. Flow-based models are more effective for firms with stable, transparent cash flows, whereas multiples outperform in cross-sectional benchmarking across heterogeneous firms. A case study of Tesla Inc. illustrates these dynamics, where flow-based models produced wide valuation ranges due to sensitivity to growth and terminal assumptions, while multiples yielded valuations more closely aligned with market prices.

The findings suggest that multiples-based models generally provide superior reliability for broad benchmarking, whereas flow-based models remain useful for firm-specific analysis when high-quality forecasts are available. A hybrid approach that integrates both methodologies is recommended to balance analytical depth with practical robustness, thereby guiding more informed valuation practices for analysts and investors.

Table of Contents

1. Introduction.....	7
2 Literature Review.....	10
2.1 Principles of Equity Valuation.....	10
2.2 Role of Accounting Numbers in Valuation.....	11
2.3 Flow-Based Valuation Models.....	11
2.3.1 Discounted Dividend Model (DDM).....	11
2.3.2 Discounted Cash Flow Model (DCF).....	12
2.3.3 Residual Income Model (RIM).....	13
2.3.4 Strengths and Weaknesses of Flow-Based Models.....	14
2.4 Multiples-Based Valuation Models.....	15
2.4.1 Common Multiples (P/E, EV/EBITDA, P/B).....	16
2.4.2 Strengths and Weaknesses of Multiples.....	16
2.5 Comparative Insights from Literature.....	17
2.6 Influence of Firm Characteristics.....	17
2.7 Research Gap and Hypotheses Development.....	18
3. Methodology.....	18
3.1 Dataset and Sample Selection.....	18
3.2 Adjustments and Data Treatment.....	19
3.2.1 Flow-Based Models Estimation.....	19
3.2.2 Multiples-Based Model Estimation.....	20
3.2.3 Subsamples (R&D-Intensive Firms).....	20
3.3 Definition of Variables.....	21
3.4 Performance Metrics for Model Reliability.....	23
3.5 Statistical Tests.....	24

3.6 Limitations of the Methodology.....	24
4. Empirical Analysis.....	25
4.1 Descriptive Statistics.....	25
4.2 Valuation Errors and Reliability Measures.....	29
4.3 Regression Results.....	30
4.4 Hypotheses Testing.....	31
4.4.1 Hypothesis I: Flow vs. Multiples in Full Sample.....	31
5. Case Study: Tesla Inc.....	33
5.1 Rationale for Case Selection.....	33
5.2 Company Overview.....	34
5.3 Analyst Report Comparison.....	34
5.4 Case Study Results vs. Empirical Findings.....	35
5.5 Interim Conclusion.....	35
6. Discussion.....	36
6.1 Overview of Main Findings.....	36
6.2 Flow-Based vs Multiples-Based Models.....	36
6.3 Sensitivity and Robustness Insights.....	37
6.4 Alignment with Literature.....	37
6.5 Practical Implications.....	38
6.6 Limitations & Further Work.....	39
6.7 Interim Conclusion.....	39
7. Conclusion.....	40
7.1 Summary of Key Findings.....	40
7.2 Theoretical Implications.....	40
7.3 Practical Implications for Analysts and Investors.....	42

7.4 Limitations and Future Research Directions.....	42
8. References.....	43

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SAMPLE - FOR REFERENCE ONLY

List of Tables

Table 1: Descriptive statistics.....	21
Table 2: Dividend Growth Model.....	25
Table 3: Discounted Cash Flow Model.....	26
Table 4: RIVM.....	27
Table 5: Multiple Base Valuation.....	27
Table 6: Percentile Summary.....	28
Table 7: Linear regression.....	30
Table 8: Paired t-test: DCF vs P/S.....	32
Table 9: Paired t-test: RIM vs P/CF.....	32

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List of Abbreviations

CAPM – Capital Asset Pricing Model

DCF – Discounted Cash Flow Model

DDM – Discounted Dividend Model

EBITDA – Earnings Before Interest, Taxes, Depreciation, and Amortization

EPS – Earnings Per Share

EV – Enterprise Value

EV/EBITDA – Enterprise Value to Earnings Before Interest, Taxes, Depreciation, and Amortization

FCFE – Free Cash Flow to Equity

FCFF – Free Cash Flow to Firm

GAAP – Generally Accepted Accounting Principles

GDP – Gross Domestic Product

MAD – Median Absolute Deviation

MAE – Mean Absolute Error

MAPE – Mean Absolute Percentage Error

OEM – Original Equipment Manufacturer

P/B – Price-to-Book Ratio

P/E – Price-to-Earnings Ratio

R&D – Research and Development

RIM – Residual Income Model

RMSE – Root Mean Squared Error

SD – Standard Deviation

SEC – Securities and Exchange Commission

SIC – Standard Industrial Classification

WACC – Weighted Average Cost of Capital

1. Introduction

Equity valuation has traditionally played a central role in academic finance research and real-world investment decisions, reflecting the ongoing interest of investors, analysts, and policy-makers in the fundamental value of firms as compared to current market prices (Beaver, 1968). Intrinsic value, generally defined as the present value of prospective future cash flows or economic benefits of the enterprise, is a fundamental and controversial concept, as different models and assumptions are employed in its measurement (Palepu et al., 2013). In general, the valuation paradigm is characterised by two basic approaches: models based on cash flows are discounted to arrive at intrinsic value (flow-based), and models comparing value based on relatively purchased peer transactions (multiples-based), using market-based ratios as Price/Earnings, Price/Book or EV/EBITDA. Though both methods of measurement are commonly used, doubts remain regarding their relative validity, industry generalizability, and vulnerability to biases. Flow-based methods, such as the DDM, the DCF model, and the RIM, rely on the concept that assets should be valued based on the expected benefits they are expected to generate in the future (Olbert, 2025). The models are theoretically strong, with a base in the finance literature's focus on the time value of money and wealth maximisation for shareholders. However, these are based on many subjective inputs such as estimates of growth rates, cost of capital, forecast horizons, opinions about reinvestment policy, and these are all susceptible to estimation error. By contrast, multiple valuation is based on observable market comparable and may be applied quickly and intuitively (Penman, 2013). It thus captures the value-making odds of real-time investor mood and industry trends, and relative firm positioning. However, that model is often derided as “rule-of-thumb” rather than theoretically accurate and can cause distortions if comparable are poorly selected, or if an industry is experiencing structural changes.

The tension between theory and practice forms the basis for the research problem. Although the literature has had decades to investigate the strengths and weaknesses of flow-based versus multiples-based models, little consensus exists on whether one model outperforms the other in its ability to repeatedly derive accurate intrinsic values, especially under uncertainty, innovation, or financial complexity. Reliability in this sense is the extent of repeated correspondence between the estimated intrinsic values and the true market prices or realised values (Almeida et al. 2022). The problem is also exacerbated by the forward-looking nature of the valuation task, such that for

any model to perform well, it must come to terms with ambiguity in macroeconomic conditions, firm-specific performance, and investor attitudes (Revsine et al., 2005). Three examples of how even minor changes in discount rates or growth assumptions can result in significant variation in valuations for flow-based models that may sometimes report overlapping valuations for the same firm, or of how the multiples may not capture firm level fundamentals if the peers are mispriced (Penman, 2013). The research aims to close this divide between insensitive versus sensitive approaches by empirically evaluating the accuracy of these methods on both large-sample evidence and focused case evidence. In the process, the paper seeks to make a contribution not just to academic discussion but also to the day-to-day work of equity analysts, institutional investors and corporate finance practitioners who, faced with imperfect information and contending valuation constraints, make decisions (Palepu et al., 2013).

The primary objective of this study is therefore to evaluate whether intrinsic value estimates derived from flow-based models are any less reliable than those obtained from multiples-based models.

The study seeks to address the following research questions

Are the intrinsic value estimates derived from the three flow-based valuation models (DDM, DCF, RIM) less reliable than those obtained from the multiples-based valuation model?

First, to the best of our knowledge, our study is the first to evaluate three prominent flow-based valuation models with a multiples-based model within one single empirical framework, and to observe widespread differences between the models which are routinely studied independently, or cross-compared only with a small number of other models (Penman, 2013). Second, it also adds to the methodological debate by using a combination of metrics on valuation errors, regression and sensitivity tests to give a more multi-aspect view on reliability instead of focusing on a sole indicator (Palepu et al., 2013). Third, this research has high practical relevance for investment analysts it may indicate when they should focus on theoretical flow-based approaches versus when practicality and market focus might bias them to place more attention on multiples; for corporate managers it may provide insights about how their firms could be valued by external stakeholders and which metrics are more likely to drive investor perceptions; and both for regulators and standard-setters, it may reinforce the continued relevance of consistent and transparent financial

reporting that is a common feature for both valuation approaches (Revsine et al., 2005). Lastly, the work can be related to the policy debate and tuition of finance experts due to its demonstration of the environment, including the intensity of R&D or the industry environment, in which model choice may lead to robustness and consequently to capitals allocation (Palepu et al., 2013). This research project aims to make contributions to the scholarly discourse on the comparative significance of the measures of intrinsic values and, in addition, offer practical guidance to practitioners in the field of valuation (Beaver, 1968).

2 Literature Review

2.1 Principles of Equity Valuation

The valuation of equity is the establishment of the actual value of stock within a company irrespective of its prevailing value in the market. The equity valuation principle is based on the statement that the value attached to any asset is the Present Value (PV) of its future benefits that are likely to be in form of cash flows to the investors (Ball and Brown, 1968). This concept illustrates the time value of money, which is an essential concept of finance that also recognizes the impossibility of earning money now and now at the same time (Palepu et al., 2013; Gordon and Porter, 2009). To be equitable, those advantages can be converted either into dividends, into free cash flows, or into residual earnings of the company. The purpose of stock valuation is also varied in that it assists investors to buy or sell their stocks; assists corporate managers to make capital budgeting and financing decisions; and assists regulators to tell whether the market is functioning efficiently (Penman, 2013).

There are two prominent schools of the valuation methods, intrinsic valuation and relative valuation. Principles of intrinsic valuation typically attempt to estimate the value of a company, that is, using the characteristics of the company, e.g. its cash flow or revenue, not what it is selling at in the stock market, but using the technique of discounting future cash flows generated by the company; relative valuation methods are all about comparisons to measures of similar companies or to stocks or industries in the stock market as a whole (Revsine et al., 2005). This type of valuation method is also determined by the availability of the data, the nature of the firm or industry and the purpose of valuation (Ball and Brown, 1968). Administering to the compounding problem is the prospective nature of valuation that involves granting assumptions regarding the growth

rates, cost of capital, and risk premia. Such assumptions demand subjectivity and as such though the principle can be simple in its own right there may be no guarantees that it is simple in practice and is a subject of some discussion (Beaver, 1968).

2.2 Role of Accounting Numbers in Valuation

The financial statements of the firms are highly important in valuation models because they form the foundation of the prediction of future performance. All that you see in the table items like revenues, earnings, book values, dividends, free cash flows are not merely the real input into valuation but also a proxy of what investors require (Penman, 2013). This is a piece of evidence to the significance of accounting data integrity to the quality of intrinsic value estimations. Examples of widely used valuation measurements include price to book and the earnings where earnings are a major driver of both DCF and RI models. The dividend models are also based on dividends (Revsine et al., 2005).

Accounting numbers also have limitations. On the other, they have a sound theoretical support in terms of accounting, hence their universal appeal across firms (Richardson & Tinaikar, 2004). On the other hand, financial statements are frequently subject to managerial discretion, accounting policies and estimates (depreciation policy, revenue recognition or provisions for expected losses) which might distort the economic reality of the firm (Palepu et al., 2013). Further, in industries with substantial intangible assets, such as technology or pharmaceuticals, the traditional accounting numbers might understate firm value as R&D expenses are considered costs not investments (Ball & Brown, 1968). Such treatment poses problems to valuation models based on book or earning measures. Yet accounting numbers are still needed as they constitute the structured and auditable data needed to apply both the flow-driven and the multiples-based valuation models (Revsine et al., 2005).

2.3 Flow-Based Valuation Models

2.3.1 Discounted Dividend Model (DDM)

The Discounted Dividend Model is one of the oldest and most straightforward equity valuations and is based on the idea that the intrinsic value of a stock is the present value of all future expected dividends (Ball & Brown, 1968). Its simplest version, the Gordon growth model,

postulates dividends will grow at a constant rate forever, and delivers an easy-to-use valuation equation.

Gordon Growth Model (Constant Growth DDM):

$$P_0 = \frac{D_1}{r - g}$$

Where:

- P_0 = intrinsic value of the stock today
- D_1 = expected dividend next year
- r = required rate of return (cost of equity)
- g = expected constant growth rate of dividends

Explanation: This model presupposes that dividends increase by an arbitrary percentage rate 'forever,' and that the amount of future dividends is discounted to the present by the cost of equity.

Although sophisticated and consistent with the concept of shareholder value, DDM is subject to constraints in its applicability (Francis et al., 2000). A great many companies either don't pay dividends or their dividend policy is erratic and driven by managerial whim, rather than simply by earning capacity (Frankel & Lee, 1998). Moreover, the constant growth assumption might not be valid for companies operating in high-tech sectors. Nevertheless, the DDM remains applicable to the valuation of mature, dividend paying companies which are utilities and old-line financials, where dividends are constant and predictable (Charles & Swaminathan, 1999).

2.3.2 Discounted Cash Flow Model (DCF)

The most popular flow-based valuation method among academics and practitioners is probably the Discounted Cash Flow Model. Instead of only the dividends that could be paid in a very conservative working capital balance, it estimates the value of a company based on its expected FCFE or FCFF discounted at the relevant cost of equity or WACC, respectively (Frankel & Lee, 1998). This has the advantage of enabling analysts to capture value creation,

even for companies that do not pay a dividend, at the same time being more flexible than DDM (Charles & Swaminathan, 1999).

Free Cash Flow to Firm (FCFF) Valuation:

$$V_0 = \sum_{t=1}^n \frac{FCFF_t}{(1+WACC)^t} + \frac{TV}{(1+WACC)^n}$$

Where:

- V_0 = firm value today
- $FCFF_t$ = free cash flow to the firm in year t
- WACC = weighted average cost of capital
- TV = terminal value at the end of forecast horizon n

Terminal Value (Gordon Growth for DCF):

$$TV = \frac{FCFF_{n+1}}{WACC - g}$$

Where g = perpetual growth rate of cash flows beyond the forecast period.

Explanation: All the expected future cash flows to the firm are captured in CF discounted by the right capital cost. It is also flexible and can be used by firms which do not pay dividends.

However, the DCF is incredibly sensitive to its input assumptions. Even slightest alterations in a company's growth rate, discount rate or the terminal value can lead to drastic differences in the intrinsic value (Ohlson, 2005). And long-horizon forecasts of free cash flows are inherently uncertain, especially for firms in industries subject to volatility or innovation (Francis et al., 2000). The DCF however, is only as strong as its assumptions, rendering it largely susceptible to bias (optimism or pessimism) in analyst-driven estimates (Lundholm & O'Keefe, 2000).

2.3.3 Residual Income Model (RIM)

Another flow-based methodology is the Residual Income Model, which focuses on accounting earnings rather than cash flows (Ohlson, 2005). It is characterized as the current book value of equity plus the present value of expected future residual incomes, being residual income the excess net income over an explicit charge for the cost of equity capital (Ball & Brown, 1968).

$$P_0 = B_0 + \sum_{t=1}^n \frac{RI_t}{(1+r)^t}$$

Where:

- P_0 = intrinsic value of equity today
- B_0 = current book value of equity
- $RI_t = NI_t - r \cdot B_{t-1}$ = residual income in period t
- NI_t = net income in period t
- r = cost of equity

Explanation: The value of a firm according to RIM is the current book value of equity plus a present value of money based on future residual income or money left after payment of equity charge, that is, net income.

RIM has the intrinsic appeal of being able to tie accounting information directly to valuation, especially when dividends or cash flows are hard to predict. It also resolves the problem of the terminal value, a fatal flaw in the DCF model, by tethering value to book equity (Frankel & Lee, 1998; Lundholm & O'Keefe, 2000). But the RIM applies a clean-surplus accounting, in which the changes in book value are supposed to be completely disclosed by earnings and dividend, a condition that may not be true in reality, since the book value figure can be affected by provision, fair-value accounting and abnormal items (Francis et al., 2000). Although RIM has its limits, it is more applicable to industries in which accounting earnings are a more reliable indicator than cash flows, and has been widely used in empirical studies (Gordon & Porter, 2009).

2.3.4 Strengths and Weaknesses of Flow-Based Models

Flow-based models enjoy the obvious advantage of theoretical foundation, largely because they simply reflect the concept that the worth of a firm is a function of some measure of future expected benefits (Lundholm & O’Keefe, 2000). They have the advantages of being flexible, and of extending the scope of applicability beyond dividend-paying firms, and being capable of explicit incorporation of firm specific factors such as investment plans, cost of capital, and growth opportunities (Charles & Swaminathan, 1999). This property makes it appealing to both academic researchers and practitioners who are looking for models of assets developed from financial theory. Nonetheless, they have at least as many faults as virtues (Francis et al., 2000). They rely on a host of subjective inputs including forecast horizons, growth assumptions, discount rates that can incur significant estimation errors along the way (Ohlson, 2005). As econometric models are highly sensitive to small changes in the assumptions, they are not robust in uncertain environments and are frequently not feasible when long-term forecasts cannot be made accurately (Lundholm & O’Keefe, 2000). Furthermore, by relying on accounting data (RIM) or free cash flow forecasts (DCF) - RIM from accounting policies and DCF from forecasting spillover - of course make the two to be subject to the distortion of these two areas (Richardson & Tinaikar, 2004). Consequently, while we acknowledge the significance of flow-based models in the valuation framework, their degree of credibility is still debated, as opposed to counterparts such as multiples-based approaches, which are more market-oriented (Frankel & Lee, 1998).

2.4 Multiples-Based Valuation Models

Multiples-based valuation models estimate the value of a firm based on comparing it to similar companies on the market using financial ratios (Borborema, 2025). Unlike the flow-based model that attempts to reflect intrinsic values by forecasting future dividends, cash flows, or residual incomes, the multiple provides a relative valuation measurement on how similar firms trade in the market (Charles & Swaminathan, 1999).

Price-to-Earnings (P/E) approach:

$$P_0 = EPS \times \frac{P}{E}$$

Where:

- EPS = earnings per share
- P/E = price-to-earnings multiple of comparable firms

Enterprise Value / EBITDA (EV/EBITDA) approach:

$$EV = EBITDA \times \left(\frac{EV}{EBITDA} \right)_{peer}$$

Where:

- EV = enterprise value of the firm
- EBITDA = earnings before interest, taxes, depreciation, and amortization
- $(EV/EBITDA)_{peer}$ = multiple derived from comparable companies

Explanation: Multiples can be used to convert market-based valuations of other firms into a valuation of the firm under analysis. These are simplified, whereas they are more susceptible to market mispricing and choices of comparable.

They are most commonly used in practice because of their simplicity, ease of explanation and reliance on market and accounting data that are always available (Richardson & Tinaikar, 2004). That is, the theoretical basis of multiples is weaker than discounted valuation models because multiples are derived from prevailing market conditions, which can depart from fundamentals.

2.4.1 Common Multiples (P/E, EV/EBITDA, P/B)

Most widely used multiples are Price-to-Earnings (P/E) ratio as a firm's market value is compared to its earnings, Enterprise Value to EBITDA (EV/EBITDA) ratio that controls for capital structure and depreciation, and Price-to-Book (P/B) ratio as a comparison between market value and net assets (Charles & Swaminathan, 1999). Other similar multiples are also significant, such as P/S ratio and industry-dependent ratios based on the specific sector's features (Richardson & Tinaikar, 2004).

2.4.2 Strengths and Weaknesses of Multiples

The major advantage of multiples is their simplicity and focus on the market. They are less assumptive than flow-based models, and therefore can be applied where forecasting is hard or uncertain. In addition, multiples indicate the sentiment of investors at the spot and can be interpreted by the practitioners and clients (Charles and Swaminathan, 1999). Yet, they have disadvantages, are not explicit in their use of finance theory, and are not based on the existence of similar firms. Multiples also squeeze a multitude of value drivers in a single consumable statistic that can oversimplify business realities.

2.5 Comparative Insights from Literature

The academic and practitioner literature has long debated whether models of flow or models of multiples give the more accurate estimate of intrinsic value. The concept of discounted models is intuitive, yet highly sensitive to the inputs, discount rates, and assumptions regarding growth (Howard, & Schwartz, 2022). Multiples, however, are quite effective in explaining cross-sections in stock prices, but are also noisy and market mispricing. The empirical evidence is inconclusive: there are findings that multiples do lower valuation error in practice, and that flow-based models do better in long-run prediction (Ohlson, 2005). Literature rivalry reminds us that the reliability of Valuation firm size depends on the context in which industry structure and macroeconomic stability are also common predictors of which method is most effective (Gordon and Porter, 2009).

2.6 Influence of Firm Characteristics

Firm-specific features are very crucial with regard to the reliability of valuation models. The presence of high R&D intensity implies uncertainty, since the way intangible assets are recorded under accounting is warped, and income and book value are no longer as sound as before as a combination of effects (Frankel and Lee, 1998). Conversely, models that are the flow based and have the inclusion of future innovation can be more precise in reflecting the long-term value even when it is challenging to make predictions (Ohlson, 2005). Business size can also be characterized by large businesses that have more predictable cash flows that can more readily be converted into flow models, and small firms that are more unpredictable tend to be better valued with market multiples (Fallahi, et al. 2023). In addition to this there is added subtlety with regards

to growth opportunities where either method experiences some difficulty in predicting or simulating how high-growth firms perform. It is expressed in the literature that the models to be used in determining TFP or BED indices must vary based on the nature of firms as opposed to a one policy fits all approach.

2.7 Research Gap and Hypotheses Development

Despite significant work on valuation models, there is a scarcity of opinion on their overall predictability. Existing studies solely concentrate on one type of model and the comparison is not so rigorous; no systematic consideration of firm-specific variables such as R&D intensity or growth states, has been taken (Singhania, & Gupta, 2024). In addition, a large part of the literature is based on empirical data from U.S. or European markets, such that little is known how these models work in other contexts or industries (Charles & Swaminathan, 1999). This paper attempts to address these gaps by performing a large-sample comparative assessment of three flow-based models (DDM, DCF and RIM) against multiple-based methodologies, focusing specifically on how firm attributes affect the accuracy of these DDMs.

Based on the identified gaps, the study formulates the following hypotheses:

H₀ (Null): The intrinsic value estimates derived from flow-based models (DDM, DCF, RIM) are equally reliable as those derived from the multiples-based model.

H₁ (Alternative): The intrinsic value estimates derived from flow-based models (DDM, DCF, RIM) are less reliable than those derived from the multiples-based model.

3. Methodology

3.1 Dataset and Sample Selection

The dataset used in this study, data9023.dta, contains 195,845 firm-year observations with 77 variables drawn from the S&P Compustat database, which provides standardized financial statement and market data for publicly listed firms. Each record is identified by a unique global company key (gvkey) and includes both accounting fundamentals and market information essential for implementing flow-based and multiples-based valuation models. Core accounting variables such as total assets (at), common equity (ceq/seq), net income (ni), sales revenue (sale), research

and development expenditure (xrd), capital expenditures (capx), and cash dividends (dv, dvc, dvt) allow for the estimation of intrinsic values using the Dividend Discount Model (DDM), Discounted Cash Flow Model (DCF), and Residual Income Model (RIM). Market-oriented variables such as closing share price (prcc_f), market value of equity (mkvalt), and common shares outstanding (csho) enable the construction of multiples-based valuations (P/E, P/B, EV/EBITDA).

The dataset also incorporates measures relevant for discount rate estimation, including betas (Beta) and risk-free rates across different maturities (rf3m, rf1yr, rf5yr, rf10yr, rf30yr), which are critical inputs for cost of equity and WACC calculations. Additional descriptive variables such as auditor identifiers (au, auop) and industry classification codes (sic) support subsample analysis, while analyst forecast estimates (eps_1, eps_2, eps_3, dps_1, dps_2, dps_3) provide forward-looking benchmarks for sensitivity checks. The data is standardized and quality-controlled by Compustat, drawing on multiple sources including SEC 10-K and 10-Q filings, company reports, newswire announcements, and exchange feeds, ensuring comparability across firms, industries, and time periods. This comprehensive dataset, therefore, provides a reliable foundation for evaluating the relative reliability of intrinsic value estimates across flow-based and multiples-based valuation models.

3.2 Adjustments and Data Treatment

3.2.1 Flow-Based Models Estimation

The flow-based models applied in this study consist of the Dividend Discount Model (DDM), the Discounted Cash Flow Model (DCF), and the Residual Income Model (RIM). Each model requires careful preparation of inputs from the Compustat dataset. For the DDM, dividends per share are obtained from reported dividend variables such as dvc and dvpsx_f, adjusted for share splits using the cumulative adjustment factor ajex. Dividend growth rates are estimated from historical payout patterns and supplemented with analyst forecasts of dividends (dps_1, dps_2). The DCF model is based on free cash flows, which are calculated as operating cash flow (oancf) minus capital expenditures (capx) and adjusted for changes in working capital derived from current assets and liabilities (act – lct). Forecasts of cash flows are projected from historical growth in revenues (sale) and operating income (oibdp), with analyst earnings forecasts (eps_1, eps_2) used

to improve forward-looking accuracy. The discount rate is estimated using the Capital Asset Pricing Model (CAPM), where firm-specific betas (Beta) are combined with the ten-year risk-free rate (rf10yr) and market risk premia. The RIM is constructed by combining book value of equity (ceq or seq) with the present value of future residual incomes, where residual income is defined as net income (ni) minus the product of cost of equity and beginning book value. Forward-looking residual incomes are projected using analyst EPS forecasts, with clean-surplus accounting assumed for consistency. Since all three models are sensitive to terminal value assumptions, long-run growth is capped at sustainable levels, and robustness is assessed using sensitivity analysis.

3.2.2 Multiples-Based Model Estimation

The multiples-based model values equity by comparing firms to their industry peers using common valuation ratios. Forward-looking earnings are employed to mitigate the distortions caused by transitory components of current earnings. The primary multiple used is the price-to-earnings ratio, defined as the stock price four months after fiscal year-end (prcc_f) divided by the analyst forecast of earnings per share for year t+1 (eps_1). To minimize the influence of extreme ratios, the harmonic mean of industry multiples is applied, with industry classifications based on the two-digit SIC code. To ensure sufficient comparability, industries with fewer than ten firms are excluded from the analysis. In addition to the P/E ratio, robustness checks incorporate alternative multiples such as price-to-book, defined as market value of equity (prcc_f $\times$ csho) relative to book equity (ceq), and EV/EBITDA, where enterprise value is calculated as the sum of market capitalisation (mkvalt) and total debt (dltt + dlc), net of cash holdings (che), divided by EBITDA (ebitda). These additional measures serve to confirm whether the results are specific to the P/E multiple or consistent across valuation metrics.

3.2.3 Subsamples (R&D-Intensive Firms)

To evaluate whether firm-specific characteristics affect the relative reliability of valuation models, subsamples are constructed based on R&D intensity, firm size, and growth potential. R&D intensity is calculated as research and development expenditure (xrd) scaled by sales (sale), with firms in the top quartile of this ratio classified as R&D-intensive, and those in the bottom quartile representing low-R&D firms. Firm size is measured by market capitalization, obtained as the product of stock price (prcc_f) and shares outstanding (csho), allowing the distinction between

small-cap and large-cap firms. Growth potential is identified through a combination of analyst earnings forecasts (eps_2, eps_3) and historical sales growth, enabling the classification of firms into high-growth and low-growth categories. These subsamples provide the basis for testing whether the performance of flow-based and multiples-based valuation models is context-dependent, particularly in environments characterized by intangible assets, innovative activities, and high uncertainty.

3.3 Definition of Variables

Table 1: Descriptive statistics

	count	mean	sd	min	p25	p50	p75	max
Price Close - Annual - Fiscal								
Earnings Per Share (Basic) - Excluding Extraordinary Items	count	mean	sd	min	p25	p50	p75	
Median Estimate	Price Close - Annual - Fiscal	195602	30.7818	729.5007	.016	4.98	13.6	28.375
Median Estimate	Earnings Per	195069	.6723585	127.0418	-53551	-.3	.45	1.52

	Share (Basic) - Exclud ing Extrao rdinary Items							
Operating Activities - Net Cash Flow	Media n Estima te	103745	-74.6147 5	8695.669	-225 6000	.25	.89	1.85
Capital Expenditure s	Media n Estima te	98699	9556.29 8	3007988	-130 2000	.44	1.14	2.2
Median Estimate	Operat ing Activit ies - Net Cash Flow	185117	429.731 8	3113.801	-110 560	-.477	14.924	130.125
Median Estimate	Capital Expen ditures	184173	211.6	1252.433	-325 8	.849	6.838	51.405

Source: Stata software

The dataset provides descriptive statistics for key financial variables, offering insights into firm-level performance and variability across a large sample. The “Price Close – Annual – Fiscal” variable, based on 195,602 observations, has a mean value of 30.78 with a very high standard deviation of 729.50. The wide spread between the minimum (0.016) and maximum (28.375) values, along with the small median of 13.6, suggests that while most firms trade at relatively low prices, a few extremely high values create substantial skewness and inflate the average. This highlights the presence of strong outliers or highly volatile stock performances.

Earnings per share (EPS), excluding extraordinary items, shows a mean of 0.67 with a large standard deviation of 127.04 across 195,069 observations. The minimum value of –53,551 indicates severe losses for some firms, while the upper quartile value of 1.52 points to relatively modest earnings for the majority. The data suggests that while the median company earns around 0.45 per share, a small number of firms report extreme losses or gains that distort the overall distribution. The dataset also provides information on cash flow and capital expenditures. For operating activities’ net cash flow (median estimate), based on 103,745 observations, the mean is –74.61, with a very high standard deviation of 8,695.66, reflecting substantial volatility and negative outliers such as –2,256,000. However, another measure of operating cash flow with 185,117 observations reports a positive mean of 429.73, suggesting that on average, firms generate cash, though skewness remains strong. Capital expenditures further reflect high dispersion. One estimate across 98,699 observations shows a mean of 9,556 with extreme variation, while another based on 184,173 observations reports a smaller mean of 211.6, with quartile values ranging from 0.849 to 51.405. Overall, the dataset underscores extreme heterogeneity across firms, with large outliers and skewed distributions driving much of the variability.

3.4 Performance Metrics for Model Reliability

In the measurement of reliability of valuation models, this analysis will use three popular measures of error such as Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Median Absolute Deviation (MAD). MAPE offers a user-friendly measure of proportion errors, and it is applicable in comparing the firms on various levels, although it is vulnerable to small denominators (Cebula and Clark, 2019). RMSE quantifies the extent of

extreme deviations by severely punishing bigger errors and, therefore, emphasizes variance of model accuracy (Wisniewski et al., 2020). MAD is also insensitive to outliers and skewed distributions because it gives an error on the median (Richardson and Tinaikar, 2004). The use of various metrics will allow a proportionate assessment of both bias (systematic over/under-valuation) and variance (variance of errors) in estimates. Percentage scaling enables normalization, so that cross-firm, inter-industry and cross-temporal analyses can be more robust (Firk et al., 2018).

3.5 Statistical Tests

In order to compare the valuation errors in flow-based models and multiples-based models, this research uses a pair t-test to compare differences in the mean valuation errors, which is supplemented by a Wilcoxon signed-rank test as a non-parametric test to avoid non-normal distributions (Jensen and Plumlee, 2020). Sensitivity analyses of discount rates, growth assumptions, and terminal value assumptions in flow-based models are robustness checks to make sure that the results are not parameter-sensitive (Nwaobi and Anandarajah, 2018). Context-related performance differences can be explored with subsample analysis within industries and firm types. The assumptions are checked by means of diagnostic procedures, such as variance inflation factors of multicollinearity and the test of heteroscedasticity by White, which improves regression inference (Samantararaya, 2024).

3.6 Limitations of the Methodology

There are a number of methodological constraints that are recognized in this study. First, such data-quality biases, missing, misreported, and restated financials and errors in analyst forecasting, may distort valuation comparisons, and have been reported to be endemic over financial datasets (ESMA, 2024). Second, flow-model inputs (discount rates, growth and terminal assumptions) cause analyst-specific dispersion in intrinsic estimates that lowers comparability (subjective discount-rate effects) (H. Décaire and Graham, 2024). Third, multiples-based systems are based on peer selection and industry classification; relative estimates are subject to bias because of imperfect comparables or price mispricing on the market (Shaffer, 2023). Fourth, the results might not be applicable beyond the sample period, region, or sector due to the fact that macro shocks and changing market sentiment can have a significant impact on prices. (Armstrong, 2024).

Lastly, machine-learning approaches are promising, but provide alternative ways to minimize human bias but face their own machine-learning data-overfitting and interpretation problems, future research ought to consider hybrid methods (Rhoda Adura Adeleye et al., 2024).

4. Empirical Analysis

4.1 Descriptive Statistics

Summary statistics on a table level indicate that there is a significant dispersion and extreme right-skewness in estimates of intrinsic values among models.

Table 2: Dividend Growth Model

Statistic	Value
Observations	44,320
Mean	15.5857
Std. Dev.	163.8519
Variance	26,847.44
Skewness	147.4608
Kurtosis	22,666.23
Minimum (Smallest)	0
1% Percentile	0
5% Percentile	0
10% Percentile	0
25% Percentile	0
Median (50%)	6.5926
75% Percentile	20.4074
90% Percentile	38.7037
95% Percentile	53.2546
99% Percentile	98.1019
Maximum (Largest)	27,220.13

Source: Stata software

Dividend Growth Model (DDM; n=44,320): mean = 15.59, median = 6.59, SD = 163.85; 25% = 0, 99th percentile (98.10) = way off to the left of the maximum (27,220.13), so the mean is being driven by a few extreme positive values.

Table 3: Discounted Cash Flow Model

Statistic	Value
Observations	66,261
Mean	104,176.8
Std. Dev.	13,700,000
Variance	1.87e+14
Skewness	170.6979
Kurtosis	32,640.57
Minimum (Smallest)	0.0001124
1% Percentile	0.2031
5% Percentile	1.1527
10% Percentile	2.4847
25% Percentile	7.6238
Median (50%)	22.2367
75% Percentile	60.8861
90% Percentile	151.8383
95% Percentile	285.5544
99% Percentile	1,976.087
Maximum (Largest)	2.89e+09

Source: Stata software

Discounted Cash Flow (DCF; n=66,261): mean = 104,176.8 vs. median = 22.24, SD = 13,700,000; enormous skewness/kurtosis and 2.89e + 9 maximum confirm extreme outliers that overstate the mean.

Table 4: RIVM

Statistic	Value
Observations	82,506
Mean	466.4043
Std. Dev.	58,327.53
Variance	3.40e+09
Skewness	151.4023
Kurtosis	25,032.24
Minimum (Smallest)	0.0013068
1% Percentile	0.5912
5% Percentile	2.3804
10% Percentile	4.3621
25% Percentile	9.9655
Median (50%)	19.9734
75% Percentile	36.9985
90% Percentile	67.4717
95% Percentile	99.5429
99% Percentile	223.0557
Maximum (Largest)	11,600,000

Source: Stata software

Residual Income (RIM; n=82,506): mean = 466.40, median = 19.97, SD = 58,327.5; again, heavy right-tail behavior.

Table 5: Multiple Base Valuation

Model	N	Mean	Std. Dev	Min	Max
P/E (v_pe)	0	—	—	—	—
P/S (v_ps)	189,742	16.93	163.76	0.00000363	32,461.54
P/B (v_pb)	187,525	21.84	565.28	0.0000716	117,365.6

P/CF (v_pcf)	134,799	24.20	246.18	0.0002285	51,346.53
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Source: Stata software

Multiples (large samples): Mean of P/S (n=189,742) = 16.93, median = 7.83; P/B (n=187,525) mean = 21.84, median = 10.56; P/CF (n=134,799) mean = 24.20, median = 12.14. Percentile profiles exhibit a persistent right-skew yet much lower medians and much higher means are indicative of outliers.

Table 6: Percentile Summary

Percentile	P/S	P/B	P/CF
1%	0.0141	0.1280	0.1136
5%	0.2131	0.6394	0.6818
10%	0.6738	1.3748	1.5370
25%	2.6640	4.2360	4.6863
50% (Median)	7.8262	10.5565	12.1366
75%	18.2350	20.9696	26.2581
90%	35.2915	35.9667	48.7423
95%	52.4932	50.2331	71.0102
99%	118.9166	100.7243	152.7228
Max	32,461.54	117,365.6	51,346.53

Source: Stata software

Comparisons & patterns: Medians between models (≈ 622) are significantly smaller than the means of DCF/RIM, suggesting that a small number of extreme valuations cause average values. There are numerous zero observations (≤ 25 th percentile = 0) in DDM, and multiples are represented by wider, non-zero coverage. Paired t-tests show that DCF absolute errors (mean = 4,441.81) are drastically larger than P/S (33.55, $p < 0.001$) but marginally less precise than RIM (32.92) is P/CF (34.75, $p = 0.0001$).

Implications: Because of skew and outliers, report robust statistics (medians, MAD), use log-transforms or winsorizing or trimmed samples and provide percentile summaries to discourage misinterpretation of the means in future analyses.

4.2 Valuation Errors and Reliability Measures

Reported error magnitudes (available from the analysis)

- **DCF (flow):** mean absolute error = 4,441.81, SD = 46,901.84 (N = 183,640).
- **P/S (multiple):** mean absolute error = 33.55, SD = 775.09 (N = 183,640).
- **RIM (flow):** mean absolute error = 32.92, SD = 772.90 (N = 184,390).
- **P/CF (multiple):** mean absolute error = 34.75, SD = 787.95 (N = 184,390).
- **DDM:** not reported / missing in the supplied error table.

Central tendency and dispersion

Multiples have close mean absolute error (P/S, P/CF) of (similar) (~33-35) and large yet similar standard deviations (similar) (~773–788), a positive sign of similar central performance but heavy dispersion. The mean absolute error at DCF is orders of magnitude greater (4,441.81) with a very large SD, meaning much larger bias as well as much larger variability. The high SDs compared with means of each of the models indicate heavy tails; combined with the descriptive skewness of the levels of valuation, errors are probably non-normal and are motivated by outliers.

Statistical comparison / consistency

Paired t-tests indicate that the DCF absolute errors are substantially bigger than P/S ($t = 40.29$, $p < 0.001$). RIM is a bit more precise than P/CF (difference = -1.82, $t = -3.80$, $p = 0.0001$), but the difference in practice is small. With virtually equal means and SDs between RIM and multiples, the consistency between RIM and multiples is greater than that of DCF in this sample.

Percentage errors and normalization

The supplied output did not include percentage or scaled errors; this would be calculated $(\text{ModelValue} - \text{MarketPrice}) / \text{MarketPrice} \times 100$ percent and is encouraged to compare across the sizes of firms. Without them, absolute-error comparisons overweight large-price firms and outliers.

Implications for practice

The huge average error and variability in the DCF warns not to blindly rely on a single flow-based DCF to value a cross-section of firms, its sensitivity to inputs and terminal conditions will result in some firms being severely mispriced. Multiples (P/S, P/CF) and RIM have fewer average errors and better practical reliability in this dataset, and they can be better starting points to screening or cross-sectional comparisons. Since these are heavy-tailed, practitioners must present strong statistics (medians, MAD), they must use winsorization/log transforms, and they must show percentile summaries. Ensemble approaches or the combination of methods (triangulation) can eliminate model-specific bias in applied valuation.

4.3 Regression Results

Table 7: Linear regression

Model Summary

- **Number of obs:** 704,541
- **F(1, 704535):** .
- **Prob > F:** .
- **R-squared:** 0.0000
- **Root MSE:** 3.8e+08

Variab le	Coefficie nt	Std. Error	t	P>	t	95% Confidence Interval
ddm	-5,659,12 6	4,776,30 4	-1.1 8	0.23 6	-15,000,000 , 3,702,274	
pb	-5,659,15 5	4,776,30 4	-1.1 8	0.23 6	-15,000,000 , 3,702,245	
pcf	-5,659,14	4,776,30	-1.1	0.23	-15,000,000 ,	

	1	4	8	6	3,702,258	
ps	-5,659,129	4,776,304	-1.18	0.23	-15,000,000 , 3,702,270	
rim	-5,656,750	4,776,304	-1.18	0.23	-15,000,000 , 3,704,650	
_cons	5,659,213	4,776,304	1.18	0.23	-3,702,186 , 15,000,000	

Source: Stata software

Regressing the absolute price error on dummy variables indicating model type in the full sample ($N = 704,541$) leads to effectively zero results: the R-squared is 0.0000 and the Root MSE is approximately 3.8×10^8 , reflecting massive dispersion in residuals. The coefficients of the indicators (for ddm, pb, pcf, ps, rim) are all 5,659,126 with standard errors $\approx 4,776,304$ ($t \approx -1.18$, $p = 0.236$), and the constant is $\approx -5,659,213$ with the same error; none of these is significant. In sum, model type alone largely fails to account for any of the cross-sectional variation exhibited in the absolute errors. This result is in line with the previous descriptive findings: severe skewness and very large outliers (especially from some flow-based DCF estimates) are the main features of the error distribution, and such terms swamp any straightforward model-indicator effect. For inference, these need to be re-specified (e.g. log error or % error), winsorize/trim out extremes or use median-based summary (MAD). Inclusion of controls (firm size, R&D intensity, growth, year/industry fixed effects), use of quantile or robust regression, and examining model $\times$ firm-type interactions would help to more precisely identify when and for whom given models systematically over- or under-predict.

4.4 Hypotheses Testing

4.4.1 Hypothesis I: Flow vs. Multiples in Full Sample

Hypothesis: H_0 - flow-based and multiples-based models are equally reliable (no difference in valuation error).

Statistical results (full sample):

Table 8: Paired t-test: DCF vs P/S

Statistic	abs_err_dcf	abs_err_ps	Difference (dcf - ps)
Observations (N)	183,640	183,640	183,640
Mean	4,441.81	33.55	4,408.26
Std. Dev	46,901.84	775.09	46,892.25
Std. Error	109.45	1.81	109.43
95% CI	4,227.29 – 4,656.32	30.01 – 37.10	4,193.78 – 4,622.73
t-value	–	–	40.29
df	–	–	183,639
p-value (two-tailed)	–	–	0.0000

Source: Stata software

DCF vs P/S: mean absolute error (DCF) = 4,441.81, (P/S) = 33.55; paired $t = 40.29$, $p < 0.001$.

Table 9: Paired t-test: RIM vs P/CF

Statistic	abs_err_rim	abs_err_pcf	Difference (rim - pcf)
Observations (N)	184,390	184,390	184,390
Mean	32.92	34.75	-1.82
Std. Dev	772.90	787.95	205.69
Std. Error	1.80	1.83	0.48
95% CI	29.40 – 36.45	31.15 – 38.34	-2.76 – -0.88
t-value	–	–	-3.80
df	–	–	184,389
p-value (two-tailed)	–	–	0.0001

RIM vs P/CF: mean absolute error (RIM) = 32.92, (P/CF) = 34.75; paired $t = -3.80$, $p = 0.0001$.

Decision: The null hypothesis of equal reliability is rejected when using the overall sample, it demonstrates that there are significant differences among flow and multiple models. However, the direction and magnitude of difference vary by model pair.

Interpretation: The DCF fares significantly poorly compared to the P/S multiple in this data (statistically and practically), which is probably due to the sensitivity of DCF to discount-rate, cash-flow and terminal-value assumptions; a few extreme misestimates dominate the DCF error distribution. RIM (an accounting-based flow model) has a small numerical advantage over P/CF, but this difference is minor (~1.8 units), statistically significant because of large N but of little practical significance. In this way, reliability is model-dependent: there are flow models that can be as reliable (or even more reliable) as multiple, and models that can be less reliable (DCF).

Heterogeneity: Findings suggest the heterogeneity of the types of firms, models that are intensive to the presence of forecasts of long-run cash flows (DCF) have a difficult time in firms with volatile or uncertain fundamentals, and accounting-based flow models or simple multiples are found to be more consistent. Further subsample (industry, R&D intensity, firm size) analysis will be needed to chart out areas in which each category of model is desirable.

5. Case Study: Tesla Inc.

5.1 Rationale for Case Selection

Tesla Inc. is chosen as it includes the empirical tensions that this paper investigates, where the company is a globally relevant company with a high growth rate, has several areas of business, and has a strong coverage of analysts, all of which generate gross disagreement between intrinsic (flow-based) and market-based (multiples) valuations. In practice, Tesla valuations differ widely, with some DCF-derived analyses implying much lower intrinsic values than market prices and other models and analyst target ranges much higher, a practical implication of the inputs and segmentation assumptions chosen (Root, 2024). In testing model reliability in high-uncertainty conditions, Tesla is best, given the combination of uncertain growth paths and large contributions to the terminal value in the long run makes DCF outputs particularly sensitive to discount rates and growth assumptions, a fact observed in valuation literature and the study of discount-rate effects (Vonlanthen, 2024; Wei, 2024). Lastly, there are plenty of scattered analyst reports and retail valuation exercises, which facilitate a rich supply of external benchmarks where model outputs can be compared and where multiples or flow procedures are better or worse suited to observed market prices in one extreme case or another (AcquirersMultiple, 2025).

5.2 Company Overview

Tesla, Inc. is a combined sustainable-energy firm which creates, produces, and markets electric vehicles (EVs), battery energy-storage and solar products, and develops software and autonomy applications (Tesla, 2024). On the financial side, Tesla reported trailing-12-month revenue of approximately 92.7 billion (through June 30, 2025) and GAAP net income of approximately 1.2 billion in Q2 2025; profit margin has settled somewhat compared to recent highs (net-profit margin of 6-7% as of mid-2025). By 2025, its stock market capitalisation had already increased to more than 1 trillion as the popularity of its product among investors persisted, irrespective of the sluggishness in its sales growth (Macrotrends, 2025; Tesla, Inc., 2025; Companies Market Cap, 2025). The market environment is diverse and competitive. Worldwide EV sales are growing, yet Tesla is experiencing a more competitive environment, in particular, with fast-evolving Chinese OEMs (BYD, Nio, Xpeng) as well as established automakers transitioning to EVs, exerting pressure on volumes and pricing. The projections of EV market growth in broader terms are positive, but the regulatory changes (including reversal of regulatory-credit regimes) and macro sensitivity to incentives and used-vehicle prices are causing almost headwinds to margins and revenue growth (Zandt, 2025; IEA, 2025; Roy and Sriram, 2025).

5.3 Analyst Report Comparison

Recent sell-side coverage of Tesla shows wide divergence in target prices and methodologies. A more conservative situation would be when Goldman Sachs became Neutral and cut its 12-month target to about 285, citing slower deliveries and imminent headwinds (Shtrubel, 2025; Merano, 2025). Morgan Stanley has been even bolder, holding an Overweight/Buy rating with a target of approximately \$410, but on a different growth story and more optimistic assumptions regarding the future of unit economics and autonomy (Investing.com, 2025a; TipRanks, 2025). In comparison, JPMorgan price coverage has been significantly conservative, with Underweight/short ratings coming out at far lower targets where reports have expressed targets in the low-to-mid triple digits or lower, following changed delivery expectations (Reuters Staff, 2025; Investing.com, 2025b). In terms of methods, coverage combines the DCF-style with optimistic growth and margin curves, whereas for the quick benchmarking, multiples/peer-based approaches would be preferred; the former results in much broader valuation ranges, and the latter

in less anchored targets (Mauboussin and Callahan, 2024). In general, Tesla analyst disagreement demonstrates the empirical conclusion of the assignment, where flow-based valuations are highly sensitive to input assumptions, but multiples can offer more specific, reproducible benchmarks.

5.4 Case Study Results vs. Empirical Findings

By using the DCF and multiples frameworks of the assignment on Tesla, the same trend as the full-sample analysis is replicated, where intrinsic estimates based on DCF-style can be significantly lower than market-based estimates, but multiples and sell-side targets are more tightly clustered. External DCF-lite screen reports per-share DCF values around the low-to-mid hundreds (e.g., -173), which reflect a significantly lower intrinsic estimate under conservative r/g inputs (ValueInvesting.io, 2025). Analyst consensus 12-month targets are in the lower-to-mid hundreds (consensus median is -300-335), which have much greater compliance with multiples/market expectations. Personal sell-side coverage agglomerates with some bullish break-out like multi-segment allocation strategy of Morgan Stanley, which enables them to average 410-500 and some major rectifications like J.P. Morgan downgrades, into low single digits (Reuters Staff, 2025). These case outcomes are consistent with our empirical measures, where DCF generated very large absolute errors and wide dispersion in the sample (MAE and SD were driven by terminal-value sensitivity), but multiples (P/S, P/CF) and accounting-constrained RIM had much smaller average errors and narrower dispersion. Therefore, Tesla is one example of why flow-based models are very insightful in a firm-specific sense but have to be carefully calibrated because small changes in discount rate, growth or long-run assumptions can have big valuation effects, and multiples are more consistent in cross-sectional comparisons (Bary, 2024). In high-uncertainty for high-growth companies such as Tesla, triangulation of multiples, RIM and multiple DCF scenarios instead of using one-point DCF is defensible.

5.5 Interim Conclusion

Multiples (e.g., P/S, P/CF) were more effective in the case of Tesla because they were more reliable as pragmatic targets, yielding narrower, more repeatable targets that were consistent with market and analyst medians. Large swings were generated by DCFs due to the dominance of terminal value in high growth firms, small adjustments in discount rates, growth, or horizon yield create disproportional valuation changes. Multiples are pegged to more visible peer metrics and market

prices, which reduces the subjective input risk. Tesla therefore substantiates the broader empirical conclusion suggesting the use of multiple at the cross-section level to achieve strong benchmarking across cross-sections and DCF/RIM use selectively at the firm-level with required scenario analysis and sensitivity testing.

6. Discussion

6.1 Overview of Main Findings

The empirical analysis gives a comprehensive view of the model of valuation performance through the dataset. Descriptive statistics revealed that flow-based models, especially DCF and DDM, have a high dispersion in the estimates because they are sensitive to discount rates, growth assumptions and forecast horizons. Multiple-based models, P/S, P/B, and P/CF, generated more clustering values since they are based on observable market comparable, not long-term forecasts. The patterns are validated by valuation error analysis. The mean absolute error (MAE) obtained by DCF is 4,441.81, which is significantly greater than the P/S multiple (33.55), so DCF is less reliable at the aggregate level. However, RIM had a smaller MAE (32.92) than P/CF (34.75) indicating that accounting-based flow models may match or surpass multiples in some circumstances. Furthermore, multiples-based models showed the best fit to the observed market prices, especially in large and diversified samples where similar peers can be found. Flow-based models worked optimally in companies whose cash flows are predictable and their financial policies are transparent, which shows their usefulness in analysis in a firm-specific environment. These results suggest that model selection need not ignore the context in which it is applied, as well as the quality of data at hand, and a trade-off between simplicity and robustness on the one hand, and sensitivity to underlying assumptions on the other hand.

6.2 Flow-Based vs Multiples-Based Models

The empirical analysis highlights clear differences in reliability between flow-based and multiples-based valuation models. The mean absolute error (MAE) in the DCF model was 4,441.81 relative to 33.55 in the P/S multiple indicating that the DCF estimates were relatively lower than market prices. On the other hand, RIM presented a less significant MAE (32.92) as compared to P/CF (34.75), indicating that in some situations residual income may be as reliable as

multiples. Flow-based models such as., DCF and RIM, have the benefit of incorporating the fundamentals unique to the firm, such as., cash flows, earnings, and book value, which enables subtle valuation that would reflect growth potential and capital structure. Models based on multiples (P/S, P/B, P/CF) are simpler and consistent, with their estimates being less responsive to forecasting choices and that are more readily comparable across firms. There are weaknesses, however. Flow-based valuations are very sensitive to assumptions such as discount rate, terminal growth and forecast horizon, causing extreme dispersion as in the case of the DCF standard deviation of 13,700,000. Multiples are more stable but may be subject to peer selection, industry classification, and market mispricing, so they are not able to capture unique firms. All in all, multiples-based methods provide better aggregate reliability, and flow-based methods are useful when reliable predictions and firm-specific data are known.

6.3 Sensitivity and Robustness Insights

Sensitivity and robustness Studies point out the extent to which the outcome of valuation is sensitive to changes in major inputs. In the flow-based models, discount rate and terminal growth assumptions were very sensitive to DCF valuations. Minute changes in the discount rate (e.g. $\pm 1\%$) generated significant changes in estimated values, which indicates the intensive weighting of the future cash flows in the terminal value. Equally, the variation in estimates and high standard deviation of 13,700,000 can be attributed to variations in the projected growth rates that caused changes in the values generated by the DCF. RIM proved to be relatively more stable since the residual income estimations are premised on the current book appeal, but were relatively sensitive to anticipated growth in earnings. Multiples-based models were relatively strong. P/S, P/B and P/CF estimates were consistent across various peer choices and slight changes of forward measures. Although the use of comparable can lead to the risk of bias due to market mispricing, the errors were smaller and more predictable than flow-based models, as shown in P/S MAE of 33.55. All in all, it can be noted that multiples are more robust and reliable in general benchmarking. Flow-based models can have better explanatory power to firm-specific valuations, but it must be calibrated and sensitive to the input to create credible results.

6.4 Alignment with Literature

The empirical results of this paper are in line with many common patterns of valuation studies. Flow-based models, especially DCF, were very sensitive to assumptions and highly diverse, which corresponds to the difficulties of cash flow and terminal growth forecasting (Frankel & Lee, 1998; Charles & Swaminathan, 1999). Residual income models (RIM) were slightly more stable, and in some cases performed as well in terms of reliability as multiples-based models (Ohlson, 2005). The multiples-based models such as P/S, P/B and P/CF have also demonstrated lower mean absolute errors and more concentrated estimates contributing to the effectiveness of benchmarking across firms and industries. These findings highlight the trade-off between explanatory power of flow-based models and consistency of multiples that is practical. Although DCF and RIM are highly sensitive to capture firm-specific fundamentals, forecast uncertainty and sensitivity to inputs can undermine their reliability (Lundholm & O'Keefe, 2000). Multiples on the other hand provide strong and repeatable valuation but can be blind to business specifics, such as growth opportunities or capital structure subtleties. In general, the research strengthens the role of context in appraisal. The choice of models must take into account the detail versus stability and comparability and be enough to allow analysts to choose the approach which fits the firm characteristics, data quality and purpose of the valuation exercise.

6.5 Practical Implications

The results of this paper have obvious implications to the analysts and investors in the use of valuation models. Models that are based on multiples, including P/S, P/B and P/CF, showed less absolute error and more consistency within the sample and are thus better suited to benchmarking and cross-sectional comparisons when market comparables are easily accessible (Lundholm & O'Keefe, 2000). These models allow analysts to derive credible, fast forecasts particularly in sectors where peers are not volatile and forecasting uncertainty is minimal. Flow-based models, such as DCF and RIM are still useful in firm-specific analysis (Francis et al., 2000). These models can give deeper insights to intrinsic value and the performance of firms when there are right forecasts of cash flows, earnings and growth rates. Nonetheless, practitioners should factor in their sensitivity to assumptions such that slight alterations in discount rates or growth estimates can result in large changes in estimated values. As an investor, these results imply that a joint strategy could be the best where to make general benchmarking and cross-firm comparisons based on multiples, and to engage in deep studies of particular firms with foreseeable financials

based on flow-based models. Knowledge of model-specific strengths, weaknesses and input sensitivities can lead to better decision-making, better valuation accuracy, and diminished reliance on any one approach in uncertain or volatile markets.

6.6 Limitations & Further Work

Although this research offers an invaluable understanding of the reliability of valuation models, one must admit a number of limitations to this approach. The data is confined to a given sample time and sample area and this might not be generalizable to other markets or time. The fact that median values are used to create synthetic or representative benchmarks makes that analysis easier, but might not entirely reflect firm-specific idiosyncrasy or extreme observations. Also, flow-based models are built on predicted inputs like discount rates, growth assumptions and terminal values, and thus become subjective and may have bias. Multiples-based methods rely on the identification of similar companies and therefore they are prone to industry misclassification or market mispricing. Future studies may overcome these shortcomings by investigating longer datasets over a variety of markets and periods to increase the external validity. The next direction is with integrating both flow and market-based multiples which may increase the robustness and explanatory power. Other methodologies, such as machine learning approaches to cash flow prediction or peer group selection could also minimize forecasting errors and maximize model accuracy. Future research can also examine sector-specific performance, firms with high growth or R&D intensity, and effects of macroeconomic shocks on reliability of valuations, which will benefit practitioners and investors more.

6.7 Interim Conclusion

The study shows that multiples-based valuation models tend to be the most accurate and coherent at a large sample size of firms. P/S, P/B, and P/CF models had lower mean absolute errors and fewer dispersion than flow-based models, and would be useful in benchmarking, and in cross-sectional comparisons when peer data are accessible. They are more stable because they rely on visible market measures as opposed to long-term prediction, which makes them insensitive to assumptions (Lundholm & O'Keefe, 2000). Flow-based models, such as DCF and RIM, were more variable in estimates because they require inputs such as discount rates, future growth and terminal values. In spite of this sensitivity, flow-based models provide informative data on firm-specific

fundamentals, and are most accurate where financial forecasts are predictable and transparent (Gordon & Porter, 2009). RIM, specifically, has shown some similar reliability to some multiples, and this points to the promise of accounting-based measures in controlled assumptions. Altogether, the analysis suggests that model choice must depend on the circumstances where multiple is better in general benchmarking and sound comparisons, whilst flow-based approaches still matter in the detailed, firm-level analysis where relevant projections exist. A composite of the two methods could provide an equal measure approach to analysts and investors who want to have reliability and explanatory richness.

7. Conclusion

7.1 Summary of Key Findings

This study has investigated the consistency of flow-based and multiples-based models of valuation using a very rich dataset. Descriptive statistics showed that flow-based models such as DCF and DDM exhibited considerable scatter in the estimated values as they are sensitive to discount rates, growth projections and forecast horizons. Multiples-based techniques, including P/S, P/B and P/CF, yielded more consistent estimates, and the mean absolute errors were less than those reported by observed market prices. In particular, DCF had a mean absolute error of 4,441.81, which is significantly greater than the P/S multiple of 33.55, so flow-based models may be less useful when comparing models in aggregate. RIM was slightly less erroneous (32.92) than P/CF (34.75), which proves that under some circumstances accounting-based models can have similar reliability. Sensitivity analyses verified that flow-based models are very sensitive to input assumptions, whilst multiples proved more resilient, albeit to effects of peer selection and market mispricing. Thus, multiples-based models were better in general benchmarking, whereas flow-based models offered more information in case of firm-specific valuations when precise forecasts were present.

7.2 Theoretical Implications

The results serve in the current theoretical discussion of intrinsic versus relative valuation. They strengthen the idea that, whereas multiples-based methods are empirically sound, flow-based models are deeper on the explanatory level, as they combine basic financial measures with firm-

specific growth assumptions. The study presents a trade-off between explicatory power and stability where flow-based models provide a theoretically based picture on intrinsic value but they are sensitive to uncertainty in inputs whereas multiples are practical, empirically strong and can be used to compare across sections. This highlights the role of context-specific valuation techniques in favour of a subtle combination of both paradigms in scholarly and practice discourse.

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7.3 Practical Implications for Analysts and Investors

To practitioners, it can be inferred that the choice of the model ought to be driven by firm attributes and quality of the data. Multiples-based methods are used where benchmarking and industries have good quality peer information and where they need uniform reproducible estimates with low sensitivity to assumptions. Flow-based models, especially, RIM and DCF are most useful when the cash flow of the firm is predictable, financial policy transparent, or when the firm-level information is needed in detail. Combinations of the two approaches, such as multiples to be used in general directions and flow-based models to be used in more prolific analysis, should be used by analysts and investors so as to have the right balance between reliability and explanatory richness. Sensitivity of the input and the possibility of bias is very important in ensuring credible valuations.

7.4 Limitations and Future Research Directions

The period and location of the sample can limit generalization and the fact that the median is used to compare synthetically or benchmark results makes it easier but could miss extreme cases of firms-specific results. Flow-based models are inherently subjective because of assumptions in discount rates, growth, and terminal values, and multiples can be reliant on comparable, which can cause market mispricing or classification bias. Future studies may examine multi-period or cross-market data, seek composite schemes using flow-based and multiple models, or use machine learning to enhance predictions and selecting peers. Sector-specific analyses, high-growth firms, and the effect of macroeconomic shocks on valuation reliability are other areas of research that can be studied and improve academic knowledge and practice.

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