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Does the reliability of the intrinsic equity value estimates derived from a multiple-based model and three flow-based models differ?

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September, 2021

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Final Work in Academic Context presented to
Universidade Católica Portuguesa
in order to obtain the master's degree in Finance

by

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September, 2021

Resumo

A presente dissertação investiga o desempenho de um *multiple-based valuation model* e de três *flow-based valuation models* – *dividend discount model*, *discounted cash flow model* e *residual income valuation model* – na avaliação do capital próprio. Na análise são consideradas 2,856 observações de empresas públicas dos EUA entre 2005 e 2015. Cada observação é avaliada em tendência, precisão e explicabilidade utilizando *t-tests*, *Wilcoxon sign-rank tests* e regressões OLS. Contrariamente à literatura precedente, descubro que o *multiple-based valuation model* apresenta melhor desempenho em todas as medidas de avaliação, seguido pelo *residual income valuation model*, *discounted cash flow* e *dividend discount model*, respetivamente. Relativamente ao impacto do R&D no desempenho dos modelos, todos os modelos *flow-based* apresentam melhor desempenho ao avaliar empresas com baixo nível de R&D, enquanto que o modelo *multiple-based* detém melhor desempenho na avaliação de empresas com elevados investimentos de R&D. Não obstante, a ordem de desempenho dos modelos prevalece independentemente do teor de R&D. Para avaliar a robustez dos resultados perante as várias adversidades na implementação dos modelos, são realizadas análises de sensibilidade para o prémio de risco de mercado, taxa de crescimento, horizonte de previsão, método de seleção de empresas comparáveis e o cálculo do múltiplo de *benchmark*. A análise evidencia que a ordem de superioridade dos modelos é robusta a todas as variações, com exceção dos níveis mais baixos de prémio de risco de mercado, onde o modelo menos sensível, o DDM, supera os restantes modelos *flow-based*. Estas indagações são testadas na prática através da análise de dois relatórios *sell-side* de analistas para a empresa *The Walt Disney Company*. Em conformidade com a análise principal, os analistas preferem o modelo *multiple-based* para estimar o preço-alvo, contudo este parecer é baseado num caso individual, pelo que não deve ser generalizado. Para concluir, esta dissertação destaca a superioridade do modelo *multiple-based* perante todos os modelos *flow-based* na avaliação do valor do capital próprio numa economia moderna.

Palavras Chave: Modelos de Avaliação de Capital Próprio, Comparação de Desempenho, Relatórios de Analistas

Abstract

I investigate the valuation performance of one multiple-based valuation model using 1-year ahead consensus forecasted earnings as a value driver and of three flow-based valuation models – dividend discount model, discounted cash flow model and residual income valuation model. To conduct the analysis, 2,856 observations of U.S. public companies from 2005 to 2015 are considered. Each observation is assessed for bias, accuracy and explainability utilizing t-tests, Wilcoxon sign-rank tests and ordinary least squares regressions. Opposite to prior research, I find that the multiple-based valuation model performs best in all performance measures, followed by the residual income valuation model. The discounted cash flow model is contemplated as superior to the dividend discount model, even though they sometimes alternate their order of superiority. Concerning the impact of the R&D expenditure on the performance of the models, all the flow-based valuation models perform best in a low R&D context, while the multiple-based valuation model performs best in a high R&D context. Still, the models' performance ranking prevails regardless of the R&D expenditure. To evaluate the robustness of the results to the models' implementation issues, sensitivity analyses for the market risk premium, growth rate, forecast horizon, selection of comparable companies and the method of computing the benchmark multiple are executed, which evidences that the models' performance ranking is robust to each assumption alteration, except for the lowest levels of the market risk premium where the least sensitive model, the DDM, outperforms within the flow-based valuation models. These findings are tested in reality by analysing two sell-side equity analyst reports for The Walt Disney Company (NYSE: DIS). In line with the main analysis, the appraised analysts seem to prefer the multiple-based valuation model to estimate a target price. However, this evidence based on one individual case company cannot be generalized. To conclude, this dissertation underlines the multiple-based valuation model's superiority over all the flow-based valuation models in estimating equity value in a modern environment.

Key Words: Equity Valuation Models, Performance Comparison, Analyst Reports

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List of Abbreviations

Abbreviation	Meaning
APE	Price Scaled Absolute Prediction Error
β	Beta
BVE	Book Value of Equity
BVEPS	Book Value of Equity Per Share
CAPEX	Capital Expenditure
CAPM	Capital Asset Pricing Model
CSRP	Center for Research in Security Prices
CSR	Clean Surplus Relation
DCF	Discounted Cash Flow Model
DDM	Dividend Discount Model
DGM	Dividend Growth Model
DPS	Dividend Per Share
EBIT	Earnings Before Interests and Taxes
EBITDA	Earnings Before Interests, Taxes, Depreciation and Amortization
EPS	Earnings Per Share
EV/EBITDA	Enterprise Value to EBITDA
FBVM	Flow-Based Valuation Model
FCFE	Free Cash Flow to Equity
FCFEPS	Free Cash Flow to Equity Per Share
FCFF	Free Cash Flow to the Firm
g	Growth Rate
GAAP	Generally Accepted Accounting Principles
I/B/E/S	Institutional Brokers' Estimation System
IPO	Initial Public Offer
LSA	Large Sample Analysis
MBVM	Multiple-Based Valuation Model
M&A	Mergers and Acquisitions
MRP	Market Risk Premium

NI	Net Income
OLS	Ordinary Least Squares
P/E	Price to Earnings
P/FCF	Price to Free Cash Flow
PRC4	Stock Price Four Months After Fiscal Year End
RI	Residual Income
RIVM	Residual Income Valuation Model
r_f	Risk Free Rate
R&D	Research and Development
ROA	Return On Assets
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
St. Dev.	Standard Deviation
SVE	Price Scaled Signed Valuation Error
TV	Terminal Value
WACC	Weighted Average Cost of Capital
WC	Working Capital

1. INTRODUCTION

Valuing a company is of main significance for the company insiders and outsiders. In general, valuations are performed by analysts and investors to provide informed recommendations and make investment decisions, respectively, while the insiders' focus on valuations is to maximize the company value (Palepu, Healy et al., 2013). Various distinct valuation models exist and, although theoretically they should yield equivalent value estimates (Penman and Sougiannis, 1998; Francis et al., 2000; Liu et al., 2002), in practice they are vulnerable to implementation issues capable of creating divergences in the derived value estimates. Hence, due to the importance of assessing if different valuation models generate equivalent estimates, this dissertation aims to test whether the reliability of the value estimates computed by the flow-based valuation models (FBVMs) and the multiple-based valuation models (MBVMs) differ, where the FBVMs inspected are the dividend discount model (DDM), the discounted cash flow model (DCF) and the residual income valuation model (RIVM). Moreover, if divergences are perceived, the dissertation proposes a suggestion of which of the scrutinized models performs better.

Whilst almost all researchers acknowledge that among the FBVMs the RIVM has a superior performance (e.g., Francis et al., 2000), and that among the MBVMs the forward price to earnings multiple performs the finest (e.g., Liu et al., 2002), empirical evidence on the comparability of FBVMs and MBVMs is minimal. Thus, the juxtaposition of both model-based categories in this dissertation intends to close a gap in the literature. It should as well be recognized that most of the noteworthy research about the topic is now somehow dated, therefore this work provides more recent empirical evidence encompassing more up-to-date information, such as interest rate circumstances and economic conditions. The analysis also includes the 2008 financial crisis, which hasn't been appraised before due to the timing of the other studies. Accordingly, the benefit of this dissertation is to give an insight regarding which valuation model can bring forth more useful information for decision making and, consequently, to form a basis for which valuation model performs best in estimating equity values in a modern environment.

The dissertation is most closely related to the Francis et al. (2000) analysis, yet the following must be contemplated. While their sample data was collected from 1989 to 1993, this dissertation uses data from 2005 to 2015, which analyses a longer and more recent time horizon where contemporary economic conditions are included. Additionally, whereas their research solely examines the FBVMs, this work also inspects the MBVM in a joint analysis. Besides, this dissertation uses the database Institutional Brokers' Estimate System (I/B/E/S) and not Value Line.

Contradicting the theoretical rationale that different models should yield the same value estimations, I advocate hypotheses on the advantageousness of the valuation models, which results in the succeeding ascending ranking: MBVM, DDM, DCF and RIVM. I also hypothesise that value estimates are more reliable for companies with zero or the lowest R&D expenditure, whereby the models' performance ranking is not altered. The preceding hypotheses are assessed for three performance measures – bias, accuracy and explainability – by employing t-tests, Wilcoxon signed-rank tests and OLS regressions.

Contrary to the literature, the analysis infers that the MBVM utilizing one-year ahead consensus forecasted earnings as value driver performs best in all performance measures, which indicates that the fewer assumptions required by the MBVM in conjunction with the model's ability to capture the market sentiments are beneficial for the valuation procedure. Within the FBVMs, the RIVM has a superior performance in all measures, while the DDM and DCF perform rather poorly. Concerning the R&D analysis, all FBVMs yield less bias, more accuracy and more explanatory power in a low R&D context, while the MBVM performs better in a high R&D context, with the performance ranking prevailing in both R&D contexts. Afterward, a sensitivity analysis is conducted to assess the vulnerability of the models to the required assumptions. It demonstrates that the models' performance ranking is robust to alterations in the critical assumptions (except for lower levels of market risk premium) and that the DDM and DCF are the most robust and most vulnerable models, respectively.

The findings of the large sample analysis are compared with two sell-side equity analyst reports for the individual case of The Walt Disney Company (NYSE: DIS). In line with the aforementioned findings, the investigated analysts seem to prefer the MBVM over the FBVMs to estimate a target price. However, this evidence must not be generalized, as analysts may modify their preferences depending on the company and industry.

Hence, this dissertation complements the preceding research and augments the Francis et al. (2000) research by also including the MBVM in the analysis. Moreover, by employing a small sample analysis to investigate how practical implementation issues are addressed by analysts, this discussion does not solely focus on the theoretical performances of the models, as most of the antecedent research does.

The dissertation commences with a literature review of the connection between accounting numbers and firm value. Then, the valuation models are introduced and critically assessed based on their advantages and disadvantages. Thereafter, hypotheses are developed to be tested in the next section, the large sample analysis. This second section comprises a performance analysis of one MBVM and three FBVMs for a U.S. firms' dataset from 2005 to 2015, where the findings are scrutinized and subject to a sensitivity analysis. The final section comprehends a small sample analysis in which two sell-side equity analyst reports for The Walt Disney Company (NYSE: DIS) are examined to evaluate the utilization and implementation of the valuation models in practice.

2. LITERATURE REVIEW

The literature review provides empirical evidence on the connection between accounting numbers and equity value. The focus is on the discussion of three flow-based valuation models and the multiple-based valuation model, where their rationale, advantages, critiques, limitations and implementation issues are scrutinized. Finally, based on the empirical evidence, hypotheses are established.

2.1. Equity Valuation Principles

Valuation is the technique of converting accounting numbers and forecasts into an estimated number that represents the company's equity (Palepu, 2004). Lee (1999) states that due to the complexity and subjectiveness of the forecasting procedure, valuation is a science but also an art. Fernandez (2005) argues that valuation isn't a science, but the proclamation of an opinion formed on expectations, which requires significant knowledge about the company being valued and its industry.

Equity valuation is of main importance for company insiders and outsiders. In the insiders' perspective, firm value maximization is the managers' major objective, whereby valuing equity is key for practically every business decision involving financial management. For the outsiders, analysts and investors conduct valuations to make informed recommendations and investment decisions. Hence, equity valuation provides the foundation for numerous purposes, as well as to IPOs and M&As (Palepu et al., 2013).

2.2. Equity and Entity Perspective

Equity value can be estimated from two perspectives. The equity perspective considers solely the shareholders' claims, while the enterprise perspective considers the shareholders' and debtholders' claims (Damodaran, 2006). Although theoretically, both perspectives should yield equal value estimations, practical implementation issues may lead the perspectives to not being equivalent (Palepu et al., 2013).

Equity value can be calculated directly or through the enterprise value less net debt (where net debt is equal to debt minus cash), as the latter isn't attributable to equity holders. The equity value perspective straightforwardly estimates the value of shareholders' claims in the market, whilst the entity value cannot be easily observed because debt is usually approximated by book values (Palepu et al., 2013; Penman, 2013). This approximation can generate significant discrepancies in the debt value due to interest rate fluctuations, default risk deviations and divergences in accounting practices. However, in the real world with taxes and agency costs (i.e., financial distress cost), the capital structure impacts the company value and, consequently, the equity value. Therefore, valuing from the entity perspective is less susceptible to capital structure decisions (Schreiner and Spremann, 2007). Figure 1 is provided by Damodaran (2006) and depicts the difference between equity and entity value.

Figure 1 - Computation of equity value based on enterprise value

Damodaran (2015) argues that using debt in the valuation makes the process more arduous and the advantage of considering the capital structure can be smoothly lost over time due to changes in the firm's leverage. Thus, the author states that the equity perspective valuation is more forthright and derives more conservative estimates, regardless of the company. Furthermore, Fernandez (2005) and Schreiner and Spremann (2007) conclude that the equity perspective produces the most accurate valuations.

Henceforth this dissertation only considers the equity perspective, as Francis et al. (2000).

2.3. Relation between Firm Value and Accounting Numbers

Accounting numbers is a crucial component in valuation since the information contained in these numbers is directly incorporated into the valuation process. Even though the valuation relies heavily on accounting figures, Lee (1999) states that the accounting information is not produced to support valuations, thus it is necessary supplementary expertise to generate accurate value estimates.

Accounting numbers used in the valuation procedure include earnings, dividends and cash flows, among others. Dechow et al. (1998) state that analysts tend to employ earnings rather than cash flows because earnings provide a bigger correlation with firm value than cash flows, and thus are a better predictor of the future. However, due to their accrual component, earnings may materialize manipulations by firm managers to meet their interests, whereby the accounting standards play a crucial role in protecting market participants from possible accounting misreporting (Palepu, 2004). According to Lev (1989), earnings, the financial statements' bottom line, is the most studied figure because it depicts the most critical information from all accounting items. Therefore, earnings are further scrutinized.

Earnings represent the firm's financial performance over a particular time horizon and are accrual-based, contrary to cash flows. Nichols and Wahlen (2004) argue that, in theory, earnings represent a change in shareholders' value. Remarkably, important researchers that constitute the foundation of the finance literature, as Graham et al. (1962), Fama (1965) and Miller and Modigliani (1966) proclaim that earnings are the critical explanatory variable in the valuation process because a firm's intrinsic value highly depends on the earnings figure.

Beaver (1968) observes that prior to earnings announcement the trading volume is lower than normal, while after the announcement it is above normal with significant price reactions. These findings suggest that before the announcement date, investors defer their trading decisions until the information is public, which validates the hypothesis that earnings incorporate relevant information. In fact, Ball and Brown (1968) analyse the impact of expected and unexpected elements of earnings changes on stock prices and discover that a negative (positive) surprise results in lower (higher) stock returns. They culminate that although earnings can influence the stock price, they are not timely since most of the annual reports' information is accurately anticipated by the market. However, Dechow (1994) concludes that earnings are timelier than cash flows, with the latter having difficulties in describing firm performance due to timing and matching issues.

More current evidence on the earnings and stock price connection is provided by Nichols and Wahlen (2004). They detect that companies with increasing earnings have bigger abnormal returns than companies with decreasing earnings. Furthermore, they claim that earnings yield more pertinent information than cash flows, which demonstrates the relevance of accrual information.

Conversely, criticism concerning the usage of earnings in valuation exists. Lev (1989) asserts that earnings possess scarce explanatory power of stock returns. The researcher argues that earnings dissimilarities due to accounting treatments, together with earnings manipulation and investor irrationality, result in a weak correlation of earnings with stock returns. Indeed, Burgstahler and Dichev (1997) and Courteau et al. (2015) find earnings management in their researches, which results in the authors arguing that estimations based on earnings can be so much misrepresented that they are no longer reliable. However, they state that accounting numbers still have a vigorous explanatory power on valuations.

To conclude, while some researchers propound that earnings and stock prices are correlated, others observe no evidence or find that value estimations can be misstated. Altogether, no consensus exists, yet accrual earnings appear more correlated to stock prices than cash flows.

2.4. Valuation Models

2.4.1. Flow-Based Valuation Models (FBVMs)

Based on a multi-period forecast of an accounting flow, by discounting all the flows to the date of the valuation using an appropriate discount rate, the FBVMs produce an estimation of the firm's intrinsic value that can be compared to the market stock price (Damodaran, 2006).

The discount rate applied, cost of equity (r_e), represents the riskiness of the projects taken by the company as well as the financing mix utilized to finance them (Damodaran, 2010). In particular, the r_e calculation can be conducted using the Dividend Growth Model (DGM) or the Capital Asset Pricing Model (CAPM).

$$DGM: r_e = \frac{D_1}{P_0} + g \tag{2.1.}$$

$$CAPM: r_e = r_f + \beta(r_M - r_f) \tag{2.2.}$$

Where:

r_e	Cost of equity
D_1	Expected dividend payment in the next period after the valuation date
P_0	Current share price at the valuation date
g	Growth rate
r_f	Risk-free rate
β	Beta (measure of systematic risk)
r_M	Expected return from the market
$(r_M - r_f)$	Market risk premium (expected return from the market above r_f)

Companies are expected to have an infinite lifetime (which might not be always true, as in cases of bankruptcies and takeovers). However, the process of forecasting for a long horizon is arduous and vulnerable to errors. Therefore, as accounting forecasts become less reliable the further they are into the future, these models conjecture a terminal value (TV) at the end of the forecast horizon, which portrays the value of all flows beyond the explicit forecast horizon by assuming that the value driver will grow in perpetuity. Consequently, the FBVMs depend on assumptions such as discount and growth rates, where the latter is the fixed rate that represents the rate at which the business will grow forever after the forecast horizon (Damodaran, 2006). Assuming a constant growth rate in perpetuity helps to simplify the FBVMs equations and reduces the vulnerability of errors caused by longer forecasts (Palepu et al., 2013).

$$TV = \frac{E_t[VD_t]*(1+g)}{r_e - g} = \frac{E_t[VD_{t+1}]}{r_e - g} \qquad (2.3.)$$

Where:

TV	Terminal value
$E_t[VD_t]$	Expected value driver at the valuation date
g	Growth rate
r_e	Cost of equity
$E_t[VD_{t+1}]$	Expected value driver 1 year after the valuation date

Although different FBVMs explain the valuation process using different approaches with distinct sources of value creation (e.g., dividends, cash flows or residual income), all the FBVMs are theoretically equivalent in the sense they estimate the firm's intrinsic value by discounting the forecasted future accounting flows to the present, which should result in equivalent value estimates regardless of the model employed (Francis et al., 2000). In the following sections, the three FBVM are analysed.

2.4.1.1. Dividend Discount Model (DDM)

William (1938) establishes the foundation for the DDM based on the idea that the expected payouts to shareholders (in the format of dividends) are the value driver that dictates the firm value (Penman and Sougiannis, 1998).

In theory, the value of a financial claim is the present value of the payoffs that will be received in the future by the claim holders. Thus, this model reflects the assumption that dividends received by shareholders due to their equity claims are the ultimate cash payoffs made by the firm, thereby the firm's intrinsic value is determined as the present value of the expected future dividends (Palepu et al., 2013).

According to Penman (2013), the company's share price should represent the sum of all the future dividends discounted to the present. Assuming that dividends will grow at a constant rate from the second year onwards and by employing the TV equation discounted to the valuation date, the forecasting period is shortened, which simplifies the model (Palepu et al., 2013). The DDM with the TV component is depicted in equation 2.5.

$$V_t^e = \frac{E_t[DIV_{t+1}]}{1+r_e} + \frac{E_t[DIV_{t+2}]}{(1+r_e)^2} + \cdots + \frac{E_t[DIV_{t+n}]}{(1+r_e)^n} \quad (2.4.)$$

$$V_t^e = \frac{E_t[DIV_{t+1}]}{1+r_e} + \frac{E_t[DIV_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[DIV_{t+2}]*1+g}{re-g}}{(1+r_e)^2} \quad (2.5.)$$

Where:

V_t^e	Firm's equity value at the valuation date
$E_t[DIV_{t+n}]$	Expected dividend to be paid in $t+n$ years from the valuation date
r_e	Cost of equity
n	Time in years
g	Growth rate

In fact, the DDM implementation is a straightforward process because dividends include all the payoffs between the shareholders and the firm. Thus, the valuation is conducted from the shareholders' perspective because the only important measure for a shareholder to value a firm is the actual monetary proceeds they receive from the company. Furthermore, dividends are usually quite stable and easily predictable, which makes their forecast – at least in the short-term – a relatively simple process (Penman, 2013). This model is best suitable for mature firms that pay a stable dividend.

However, the DDM is critically limited to firms that pay dividends, but the dividends paid by the firm are highly dependent on the firm's investment opportunities, in the sense that firms with several investment options (e.g., young growth firms) will prioritize investing over distributing dividends (Palepu et al., 2013). Thus, firms that do not pay dividends cannot be valued using DDM.

Additionally, Francis et al. (2000) realize that a high proportion of the DDM's valuation is tied to the TV component, which establishes that this model is highly sensitive to the difficult to estimate assumptions g and r_e. In fact, a small change in the estimations of the assumptions may result in large variations of the TV and, consequently, of the equity value. Regarding the assumptions, the dividends' constant perpetual growth rate assumption is often unfeasible. A more realistic assumption is that a change in g happens gradually over time (Damodaran, 2010).

To conclude, according to Hillier (2016), companies do not decrease (increase) dividends in bad (good) years, even if the firm is financially struggling (prospering), due to the shareholders' expectations regarding the dividends' level. This generates the main problem of the DDM, which is the lack of linkage between value creation and the accounting flow (the dividends). Since companies with reported losses still pay dividends, dividends aren't perfectly correlated with the period earnings. Therefore, DDM should only be utilized if dividends can be related to value creation and if it is feasible to properly forecast the expected dividends (Penman, 2013).

2.4.1.2. Discounted Free Cash Flow Model (DCF)

Fisher (1930) assembles the basis for the DCF. This model represents the same finance theory for the financial claims' value as the DDM, but instead of discounting dividends, free cash flows to firm (FCFF) or equity (FCFE) are discounted, which reflects the value attributable to the firm or shareholders, respectively, after the withdrawal of all investments (Palepu, 2004).

Equity valuation using the DCF can be conducted from two perspectives. Firstly, the firm's equity value can be calculated by estimating the total enterprise value – discounting FCFFs with WACC, which includes equity and debt claims – and then subtracting the net debt (debt minus cash), or by directly calculating the equity value by discounting the FCFE with r_e (Damodaran, 2010; Penman, 2013). As mentioned in section 2.2., this dissertation focuses solely on the equity perspective, thus only FCFE is scrutinized.

Damodaran (2010) states that FCFE represents the available cash flow to be distributed to shareholders after fulfilling all investment needs and debt payments. In other words, the cash flows are considered free after subtracting the cash from investments and financing from the cash from operations

(Damodaran, 2006). The FCFE can be computed by adjusting the net income for all non-cash outflows and earnings (Palepu et al., 2013).

$$FCFE_t = NI_t + D\&A_t - CAPEX_t - \Delta WC_t + \Delta Net\ Borrowings_t \qquad (2.6.)$$

Where:

$FCFE_t$	Free Cash Flow to Equity of period t
NI_t	Net Income of period t
$D\&A_t$	Depreciation and Amortization expenses of period t
$CAPEX_t$	Capital expenditure of period t
ΔWC_t	Change in Working Capital during period t
$\Delta Net\ Borrowings_t$	Change in short and long-term debt minus cash during period t

In the DCF, the value of the company is the present value of the cash flows generated by the assets that are free to be distributed to shareholders after meeting all the debt claims, discounted at the required return on business assets, the r_e (Penman, 2013; Palepu et al., 2013). Assuming again that the value driver will grow at a constant rate g after the second year and by employing the TV equation discounted to the valuation date, the equity value calculation is simplified in equation 2.8. (Palepu et al., 2013).

$$V_t^e = \frac{E_t[FCFE_{t+1}]}{1+r_e} + \frac{E_t[FCFE_{t+2}]}{(1+r_e)^2} + \cdots + \frac{E_t[FCFE_{t+n}]}{(1+r_e)^n} \qquad (2.7.)$$

$$V_t^e = \frac{E_t[FCFE_{t+1}]}{1+r_e} + \frac{E_t[FCFE_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[FCFE_{t+2}]*1+g}{re-g}}{(1+r_e)^2} \qquad (2.8.)$$

Where:

V_t^e	Firm’s equity value at the valuation date
$E_t[FCFE_{t+n}]$	Expected FCFE to be paid in $t+n$ years from the valuation date
r_e	Cost of equity
n	Time in years
g	Growth rate

Measured by the FCFE, the cash flows produced by the firm that are free to be distributed originate a dividend source. Hence, the DCF model acknowledges that firms may not pay dividends although they generate enough FCFE. However, at the end of the company’s cycle, all cash flows ultimately belong to shareholders, so over the life cycle of a company, the possible mismatch between dividends and cash flows will be cancelled out – over the firm's lifetime, dividends and FCFE should be the same under the assumption that all FCFE will be paid to shareholders. Therefore, in theory, the DCF closely relates to the DDM because cash flows are the source of dividend payout.

Nevertheless, the DCF overcomes the DDM implementation issue of dividends not capturing the true capacity of the firm to generate cash flows. As the model relies on the cash flows that are available to be distributed to shareholders (instead of dividends), the DCF is a less conservative model that is expected to produce more accurate value estimations, even for non-dividend paying companies (Damodaran, 2010).

Furthermore, Lev (1989) mentions the issue of earnings manipulation and how it can mislead practitioners doing valuations based on earnings. Thus, the DCF is less susceptible to manipulation than earnings-based models because cash flows don't include accruals, and accruals (e.g., accounts receivables) represent the earnings' part that can be misrepresented (Damodaran, 2006).

On the other hand, since companies can consummate a higher FCFE by simply reducing the CAPEX, the DCF creates an incentive to minimize investments, although they are crucial for future profitability. As investments may not have a short term effect on the firm, the model is criticized for failing to capture the added value of investments in the short-term. To address this, the forecasting period must be long enough to contemplate the CAPEX footprint (Penman, 2013).

Moreover, even if the firm reports earnings, the FCFE can be negative due to extensive CAPEX being capitalised rather than expensed (Damodaran, 2010). Hence, the DCF should only be applied whenever cash flows are positive and aligned to capital investments or the cash flows are increasing at a constant g.

Like the DDM, Francis et al. (2000) observed a high TV dependence of the DCF, which makes the model highly sensitive to the r_e and g assumptions that are difficult to estimate. Additionally, I acknowledge that the value estimate based on the DCF may not be entirely reliable because a very drastic assumption that is feasible to perfectly predict future free cash flows is needed, even though financial leverage may change over time (which will affect the FCFE) and items such as working capital are complex to identify (Damodaran, 2010).

Evidently, analysts seem to acknowledge the DCF advantages as it is widely used in the financial industry (Hand, Coyne et al, 2017).

2.4.1.3. Residual Income Valuation Model (RIVM)

The RIVM is firstly introduced by Preinreich (1938), adjusted by Edwards and Bell (1961) and rediscovered by Ohlson (1995). This model is built on an earnings' derivation as a value driver, instead of dividends or free cash flows. Indeed, earnings-based models are more consistent with the fundamental concept of the modern accounting system that includes not only cash flows, but also accruals (e.g., account receivables are an accrual – the company doesn't receive cash but recognizes the earnings), which makes earnings a key source of firm performance and a critical measure for estimating the shareholders' wealth (Lee, 1999). However, earnings approaches have some limitations, since accruals are susceptible to be manipulated and R&D expenses are mostly expensed, which decreases earnings and consequently leads to lower valuations. Therefore, on one hand, earnings probably capture better the future firm's profitability because it includes accruals, but on the other hand, they do not capture any opportunity cost and are at risk of earnings management (Nichols and Wahlen, 2004). Nevertheless, Francis et al. (2000) discover that the reliability and superiority of the RIVM are robust to divergences in the companies' accounting policies and practices, such as accruals that are ultimately reversed or the R&D accounting method.

$$Earnings = Cash\ flows + Accruals \quad (2.9.)$$

Ohlson (1995) specifies the residual income (RI) as the excess earnings over the required earnings, being the latter the earnings that could be obtained from an alternative investment. The RI proposition is based on the idea that, from the shareholders' perspective, earnings aren't enough to compensate for the shareholders' opportunity cost, therefore earnings should surpass their required earnings, otherwise shareholders will find alternative companies to invest in. For instance, dividends or positive FCFE don't assure that the RI will be greater than zero because if the company earns an accounting return similar to r_e, the RI will equal zero (Frankel and Lee, 1998).

$$RI_t^e = NI_t - (r_e * BVE_{t-1}) \quad (2.10.)$$

Where:

RI_t^e	Firm's residual income at the valuation date
NI_t	Net income of period t
$(r_e * BVE_{t-1})$	Required earnings of period t
r_e	Cost of equity
BVE_{t-1}	Beginning-of-the-period t book value of equity

Dechow at al. (1999) characterize the RIVM as a DDM restatement since one can be transformed into the other by applying the clean surplus relation (CSR). The CSR assumes a clear association between dividends, earnings and equity book value. In concrete, NI less dividends depict the capital that will be added to the company during the period, and hence the change in shareholders' equity. The CSR holds when all the variations in assets and liabilities unlinked to dividends pass through the income statement.

$$BVE_t = BVE_{t-1} + NI_t - DIV_t \quad (2.11.)$$

$$\Delta BVE_t = NI_t - DIV_t \quad (2.12.)$$

Where:

BVE_t	Book value of equity at the end of period t
DIV_t	Dividend paid during period t
ΔBVE_t	Change in book value of equity over the period t

According to Frankel and Lee (1998), if BVE and earnings are forecasted in harmony with the CSR, the RIVM can be written as BVE plus an infinite sum of discounted RI. The model proclaims firm value as the sum of the equity's invested capital added to the present value of the future RI (Lee et al., 1999).

Even though it is not returned back to shareholders, BVE is a starting point component of the RIVM value estimate because ultimately it belongs to shareholders, not to creditors. The remaining components constitute the present value of future RI that is not captured by the current BVE. Therefore, the divergence between BVE and the equity market value is captured by the discounted RI (Ohlson, 1995).

Through the assumption that RI will grow at a constant rate g from the second year onwards, the model can be streamlined using the TV equation, as in equation 2.14. (Palepu et al., 2013).

$$V_t^e = BVE_t + \frac{E_t[RI_{t+1}]}{1+r_e} + \frac{E_t[RI_{t+2}]}{(1+r_e)^2} + \cdots + \frac{E_t[RI_{t+n}]}{(1+r_e)^n} \quad (2.13.)$$

$$V_t^e = BVE_t + \frac{E_t[RI_{t+1}]}{1+r_e} + \frac{E_t[RI_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[RI_{t+2}]*1+g}{re-g}}{(1+r_e)^2} \quad (2.14.)$$

Where:

V_t^e	Firm's equity value at the valuation date
$E_t[RI_{t+n}]$	Expected RI to be paid in $t+n$ years from the valuation date
n	Time in years
g	Growth rate

RIVM has many advantages. Firstly, as Lee (1999) and Nichols and Wahlen (2004) state, earnings are the rational measure of firm performance because it takes into account further performance information that cannot be captured by cash flows, the accruals. The latter researchers assert that the incorporation of accruals solves the mismatch and timing obstacles related to the DCF. However, since earnings are vulnerable to manipulation, this advantage can be exploited by managerial discretion, which may result in a less reliable value estimate. Despite this, Francis et al. (2000) state that the RIVM is robust to divergencies in the firms' accounting practices and policies.

While Courteau et al. (2015) claim that the existence of accruals impairs the RIVM reliability, Penman and Sougiannis (1998) and Francis et al. (2000) find that the TV component represents a lower proportion of the value estimation than the others FBVMs. In fact, a large portion of the estimated value is captured by an accounting number available at the valuation date that is not based on assumptions, the BVE, which makes the RIVM estimate less sensitive to the r_e and g assumptions. Hence, they advocate that the RIVM produces more reliable estimations, making this model superior to the other FBVMs. Moreover, a larger portion of the estimated value is recognized in the near future due to the large weight of the BVE, which establishes a model more dependent on the easily predictable near future and less dependent on the more uncertain and speculative far future (Penman, 2013).

Frankel and Lee (1998) and Lee (1999) state that another major application of the RIVM is to estimate the cost of capital, since the model yields a framework to analyse the relationship between firm value and accounting numbers.

Despite these advantages, RIVM is the most complex FBVM because analysts must be aware of additional methodologies to successfully apply the model. Due to the CSR assumption, many academics state that the DDM and RIVM are theoretically equivalent, and therefore the choice between them should not matter. In concrete, Frankel and Lee (1998) proclaim that the RIVM relies on the same theory as the DDM, thus the theoretical limitations of the DDM also apply to the RIVM. Nevertheless, Lo and Lys (2000) realize that a significant number of firms that use the US GAAP violated the CSR historically, meaning that in practice CSR may not hold. The dominant justification is that not only NI, but also other comprehensive income affects the BVE (Spiceland, Sepe et al., 2013).

Overall, since analysts usually forecast earnings instead of cash flows and dividends, the RIVM is appropriate for almost all companies, regardless of industry, size or matureness (Penman, 2013).

2.4.1.4. FBVMs' Empirical Findings of the Literature

Noteworthy research is made by Penman and Sougiannis (1998) as they examine the previous FBVMs in large sample analysis. To compare firms' value estimations for distinct time horizons, the researchers utilize different valuation methods with and without terminal values. They infer that when earnings, dividends and cash flows are forecasted to infinity, the models are equivalent. However, in finite horizons, as it is done in practice, they infer the RIVM superiority because it has better accuracy, meaning that accrual earnings yield lower valuation errors than dividends and cash flows. In compliance with the theory, Penman and Sougiannis (1998) demonstrate that RI and BVE provide significant advantages over long-term dividends and cash flows forecasts. They justify this with the argument that the inclusion of accruals improves the firm's picture, as future developments can be earlier detected.

Similar to the previous researchers, Francis et al. (2000) conduct an analogous large sample analysis, with the key divergence of using ex-ante forecasts instead of ex-post forecasts. They also assert the RIVM superiority, while the DDM performs worst. Although the authors state that the three FBVMs should present similar results, they find that the RIVM consummates more reliable results and explains more price's variations than the others. They conjecture these results are due to the greater reliability of RI in conjunction with accounting-related distortions of BVEs being less severe than forecasting and calculation errors in the other FBVMs. Additionally, a lower portion of the RIVM value estimate is attributable to the more uncertain TV.

According to Dechow et al. (1999), the RIVM has minor superiority over the DDM. The authors claim that the stock prices are better explained when using models that capitalize analysts' earnings forecasts, where this greater explanatory power arises from an information problem related to analysts and investors overweighting analysts' earnings forecast information and underweighting the current earnings and book value information.

The three previous papers are contradicted by several authors. Lundholm and O'Keefe (2001) state that the RIVM and DCF produce similar value estimates when implemented correctly. The researchers argue that divergences in the theoretical equivalent FBVMs valuations result from practical implementation issues, namely inconsistent discount rates, missing cash flows and inconsistent forecasts. If implemented precisely, both models generate equal value estimations. Identically, Lee (1999) claims that the FBVMs are algebraically equivalent over infinite horizons, whilst the dissimilarities in the different models' value estimates that may arise are due to discrepancies in the assumptions, especially in the very critical TV assumption.

In the middle of both lines of findings, Courteau et al. (2001) conclude that the RIVM and DCF yield equivalent valuations when employing an ideal terminal value. Otherwise, the RIVM generates more accurate valuations.

Bernard (1995) compares the capability of dividends and RI forecasts to describe stock price variations. His findings suggest that 29% of stock price variations are explained by dividends, while 68% of the variations are explained by the incorporation of current BVE with RI forecasts.

Altogether, empirical findings seem to propose the RIVM as the most reliable valuation model among FBVMs. Nevertheless, noteworthy papers juxtapose the RIVM superiority by proposing that the three FBVMs in question are theoretically and algebraically equivalent, and that the discrepancies in their value estimations are solely resultant of inconsistencies in the models' implementation and assumptions (Penman and Sougiannis, 1998; Lundholm and O'Keefe, 2001; Demirakos et al, 2004).

2.4.2. Multiple-Based Valuation Model (MBVM)

MBVMs are broadly used among investment bankers and analysts to validate their investment advice (Demirakos et al., 2004). In fact, 99.1% of the analysts apply some sort of earnings multiple in their value estimation approach (Asquith, Mikhail et al., 2005). This universal usage is attributable to the simplicity of the valuation technique since it is an easy to calculate method with low costs associated (Fernandez, 2001). Contrary to the FBVMs that are often time-consuming, complex and sensitive to various assumptions, the

MBVMs don't require accounting flows forecasts, nor pro-forma financial statements, nor present value calculations using estimated required returns, which clarifies the MBVM attractiveness among specialists – they forfeit some of the advantages of FBVMs in favour of a procedure easier to apply that demands lower costs (Bhojraj and Lee, 2002; De Franco et al., 2015). However, since this valuation approach focuses more on the past and present than on the future, the usage of MBVMs neglects the company's growth potential and future risks.

The MBVM approach consists of the assessment of a company's stock price by anchoring the valuation process on accounting flows of the company being valued and multiplying it with a corresponding multiple that represents the flows of the comparable companies (Liu et al., 2007).

$$V_i = VD_i * Benchmark\ multiple\ (\Phi_i) \quad (2.15.)$$

$$\Rightarrow V_i = VD_i * \frac{P_j}{VD_j}(\Phi_i) \quad (2.16.)$$

Where:

V_i	Estimated value of company i
VD_i	Value driver of company i, where VD must be > 0
Φ_i	Phi, set of n comparable firms for company i, excluding i
P_j	Observed share price for the jth comparator company
VD_j	Value driver for the jth comparator company

To estimate the benchmark multiple, a multiple for each comparable firm needs to be computed. MBVMs emulate the assumption that the ratio of price over a performance measure (i.e., value driver) will revert to the comparable firms' benchmark ratio (Courteau et al., 2006). Therefore, since MBVMs depend on the current valuation of the comparable companies, this method has the propensity to capture the state of the markets (Baker and Ruback, 1999). Nevertheless, this advantage can also become a disadvantage when the valuations of the selected comparable companies are distorted into the same direction, e.g., when an entire industry is under or overvalued. Hence, the critical assumptions of this model are that markets are efficient, investors are rational and thus stocks are fairly valued; otherwise, value estimates using

MBVMs are unreliable. The aforementioned leads to the creation of a MBVM paradox: the comparable firms are believed to be correctly priced, but the firm being valued is not – if the evaluated firm is assumed correctly priced it wouldn't make sense to estimate its value (Pinto et al., 2015).

The MBVM is suitable for every firm if an appropriate value driver exists. Contrary to the FBVMs, the multiples model can be utilized for small and private firms without public information (Penman, 2013).

However, Damodaran (2006) claims that applying MBVMs assumes the existence of matching comparable firms to the evaluated firm and that a linear relationship between firm value and a specific value driver prevails. Since these assumptions aren't always fulfilled, the resultant valuations can be distorted.

A general limitation of the MBVMs is that the value driver and the benchmark multiple must be positive, otherwise the value estimate will be negative. Therefore, the MBVM isn't appropriate for start-ups with high growth but with negative operating cash flows or losses (Liu et al., 2002).

Baker and Ruback (1999) account the three major implementation issues for an effective MBVM estimation:

a) Selection of a value driver
b) Selection of comparable firms
c) Computation of the benchmark multiple

In accordance with the findings of the literature, the three implementation assumptions are going to be scrutinized in detail.

2.4.2.1. Selection of a Value Driver

Several different multiples use an extensive scope of value drivers. Generically, any firm-specific characteristic that correlates with the market price can be used as a value driver. Fernandez (2001) constructs a table to demonstrate the most utilized value drivers.

Table 1 - Most utilized value drivers by practitioners

P/E	Price earnings Ratio	**P/Output**	Price to output
P/CE	Price to cash earnings	**EV/EBITDA**	Enterprise value to EBITDA
P/S	Price to sales	**EV/S**	Enterprise value to sales
P/LFCF	Price to lev. Free cash flow	**EV/FCF**	Enterprise value to unlev. Free cash flow
P/BV	Price to book value	**EV/BV**	Enterprise value to book value
P/AV	Price to asset value	**PEG**	Price earnings (P/E) to growth
P/Customer	Price to customer	**EV/EG**	Enterprise value to EBITDA growth
P/Units	Price to units		

Multiples can be segregated into enterprise and equity multiples. According to Schreiner and Spremann (2007), equity multiples have a better valuation performance than enterprise multiples because it isn't feasible to contemplate the true debt value using market prices. Therefore, this dissertation focuses solely on the equity multiples.

The value driver selection directly influences the value estimation, so it must be done prudently. Kim and Ritter (1999) argue that no rudimentary rule applies to decide which value driver is the correct and that different value drivers may perform best depending on the firm and industry. According to Fernandez (2001), P/E and EV/EBITDA are the ones most used by practitioners, however he also highlights that the value driver choice is dependent on the industry, since each industry has its own particularities.

Overall, the value driver solely needs to fulfill two constraints. Firstly, it needs to be a positive value since equity values cannot be negative and, secondly, it must be linked to the stock price (Liu et al., 2007).

Nichols and Wahlen (2004) claim that earnings carry more appropriate information than cash flows because accruals incorporate further relevant information. Thus, the MBVMs based on earnings should lead to more reliable valuations than cash flows. However, Beaver and Morse (1978) advocate that differences in the price-to-earnings ratio may arise due to accounting practices concerning accruals and transitory items.

A crucial study about the MBVMs performance employing distinct value drivers is conducted by Liu et al. (2002) and Liu et al. (2007). The researchers find that realized earnings perform better than realized cash flows, which demonstrates the importance of including accruals in the valuation process. Additionally, their papers indicate that forward earnings have the best valuation performance, followed by realized earnings, cash flows and sales, respectively. Furthermore, a critical outcome from the authors is that the value drivers ranking is analogous to all industries and sample years, which clearly contradicts Boatsman and Baskin (1981), LeClair (1990) and Fernandez (2001) hypothesis that each industry has its ideal value driver.

Moreover, to circumvent possible drawbacks of accruals and transitory items in realized earnings, forecasted earnings should be employed because analysts usually don't forecast transitory items. Empirical evidence from Kim and Ritter (1999), Liu et al. (2002), Lie and Lie (2002) and Liu et al. (2007) indicate that forecasted earnings enhance the MBVM accuracy.

To conclude, the literature findings suggest forward earnings as the value driver that produces the most accurate valuation regardless of the industry.

2.4.2.2. Selection of Comparable Firms

Boatsman and Baskin (1981), Alford (1992) and Bhojraj and Lee (2002) proclaim that the degree of comparability between the comparable companies and the evaluated company directly influences the MBVM accuracy. Although the peers' selection is more an art than an exact science, this selection process demands huge understanding of the company being valued and its industry, as the benchmark multiple estimated from the comparable companies must reflect the multiple of the evaluated firm (Alford, 1992).

Firstly, the selection of comparable companies stands on choosing one comparable firm or a group of peer companies. Given that multiples may largely differ among firms, utilizing a set of comparable firms has the ability to decrease the outliers' effect, which consequently generates, on average, a more accurate valuation. Nonetheless, selecting only one peer firm that is the most equivalent to the company being valued produces the most accurate value estimate (Agrrawal, Borgman et al., 2010).

Palepu et al. (2016) state that the best comparable firms are the ones with the most similar financial and operating attributes to the target company. Since many firms belong to more than one industry, the matching of operating attributes is difficult to achieve, which makes the selection process arduous because firms belonging to the same industry may not be the ideal peers. Furthermore, even firms from the same industry with corresponding attributes may have divergent growth opportunities and strategies, which also negatively impacts the valuation.

In the same trajectory, Young and Zeng (2015) claim that equivalent economic characteristics, especially the accounting comparability, improves the MBVM accuracy, thus it should be contemplated in the peers' selection.

After testing seven different methods to determine the peer companies, Alford (1992) asserts that selecting comparable firms based on the industry results in equivalent accuracy as choosing the peers based on earnings growth and risk, which implies that the industry membership can capture the previously mentioned firm characteristics. In concrete, the comparable companies' selection by industry membership is conducted by selecting firms with the same first two-digit SIC code.

Boatsman and Baskin (1981) discover that the valuation is more accurate when the comparable company is precisely selected on the most analogous industry's ten-year earnings growth rate instead of selecting a random firm from the industry. Conversely, Alford (1992) does not find any upswing of splitting the industry based on earnings growth, which underpins the proposition that employing a set of firms can decrease the outliers' effect.

An unprecedented approach to select peer companies is developed by Bhojraj and Lee (2002). The authors create a "warranted multiple" for all companies, which is established by utilizing variables that influence the value driver (e.g., growth, expected profitability or risk characteristics). They conjecture that selecting companies based on the business fundamentals results in significant accuracy improvements, which can help to overcome the issue that industries aren't always explicitly delineated.

To sum up, although the comparable firms' selection is critical for the MBVMs' valuation accuracy, it is a challenging and not well-defined process. The empirical evidence advocates that comparable firms should be selected based on earnings growth and risk attributes, yet in practice specialists select peer companies according to the industry because companies from the same industry are, on average, similar regarding earnings growth and risk (Alford, 1992).

Hence, selecting a group of comparable companies from the same industry seems to be a logical and effective approach.

2.4.2.3. Computation of the Benchmark Multiple

Subsequent to the aforementioned selections, practitioners must estimate the benchmark multiple for the peer firms. The benchmark multiple computation is an averaging process of the comparable firms' multiples, however there are various averaging approaches that lead to different results, thereby this choice has a significant impact on the valuation (Agrrawal, Borgman et al., 2010).

To properly calculate the benchmark multiple, the averaging technique has to be robust to extreme values and the computation should not include the target firm, otherwise the valuation will be biased. According to Baker and Ruback (1999), there are four main averaging methods to compute the benchmark multiple.

$Arithmetic\ Mean$: $\frac{1}{n}\sum_{j=1}^{n}\frac{P_j}{VD_j}$	(2.17.)
$Value-weighted\ Mean$: $\sum_{j=1}^{n}P_j\ /\sum_{j=1}^{n}VD_j$	(2.18.)
$Median$: $median(\frac{P_j}{VD_j})$	(2.19.)
$Harmonic\ Mean$: $\frac{1}{\frac{1}{n}\sum_{j=1}^{n}\frac{VD_j}{P_j}}$	(2.20.)

Where:

P_j	Observed share price for the jth comparator company
VD_j	Value driver for the jth comparator company
n	Number of comparable companies

Even though averaging is usually contemplated as the arithmetic mean, this approach is sensitive to outliers, which may lead to an upward biased value estimation (Agrrawal, Borgman et al., 2010; Martin and Bridgmon, 2012). Baker and Ruback (1999) findings suggest that the best method is the harmonic mean because it successfully averages the yields, which are the multiples' inverse. In fact, they argue that increasing prices augments the pricing errors. Since the harmonic mean uses the yields' average, this approach gives equal weight to equal dollar investments and mathematically is always lower than the arithmetic mean, thus it produces less upward biased valuations. Furthermore, due to the MBVM construction, a small value driver results in a large multiple, which the harmonic mean also helps to tackle. Congruous with the previous authors, Beatty et al. (1999) and Liu et al. (2002) conclude that the harmonic mean generates lower pricing errors than the median or the arithmetic mean.

Contradictory findings are illustrated by Schreiner and Spremann (2007). They find that value estimations computed with median are the most precise.

Overall, empirical evidence demonstrates that practitioners must circumvent the use of the arithmetic mean because it will over-estimate firm value due to the outliers' impact. Hence, to decode this issue, the literature recommends the usage of harmonic mean or median, where the judgements between which approach performs better are divided. Nevertheless, the harmonic mean seems to be better than the median because it minimizes the effect of small value drivers.

2.4.3. Flow-Based and Multiple-Based Valuation Models Comparison

The literature comparing FBVMs and MVBMs is rather limited. Researchers usually investigate models separately, which grants a gap to compare the two categories of models concomitantly. Nevertheless, empirical evidence on the topic is depicted.

Courteau et al. (2006) find that the pricing errors of FBVMs are smaller than the ones from a price-to-forecasted earnings model. They suggest that the bigger accuracy of the FBVMs goes hand in hand with a more expensive model. Still, they conclude that a hybrid model combining FBVMs and MBVMs produces better outcomes.

Frankel and Lee (1998) culminate that the flow-based model RIVM yields a superior explanatory value than the ratios market-to-equity and book-to-price.

Imam et al. (2013) analyse Euro Stoxx 50 Index companies and their equity research reports. They demonstrate that models employing book values (i.e., RIVM) are more accurate than MBVMs.

In contrast, when Kaplan and Ruback (1995) and Gilson et al. (2000) scrutinize highly leveraged transactions, their findings suggest that the DCF and the cash MBVM result in more precise valuations.

To conclude, the empirical research comparing FBVMs and MBVMs is minimal. Hence, this dissertation aims to provide a comparison between both models' categories to determine which method is more reliable.

2.5. Influence of Research and Development Expenditures on Valuation Models

In the majority of industries, for the company to persist competitive, R&D investment is fundamental. However, prior to conduct to long-term prosperity, R&D is expensed, which results in accounting earnings figures that understate the “true” earnings (Eberhart et al, 2004). Whenever R&D is expensed, it diminishes the net and operating income, which also decreases the wealth available to be distributable as dividends. When capitalized, the R&D increases CAPEX, which decreases the free cash flow (Damodaran, 1999). Therefore, as the R&D has significant influence on accounting items employed by the models, and consequently on firm value, its influence is scrutinized.

Lie and Lie (2002) notice that current earnings are an inadequate predictor of firm value for an R&D intensive company. All models' estimations undervalue the actual value, presumably because the valuation models fail to totally recognise the growth prospects created by the R&D activities. Therefore, although R&D is an investment for the future, in the present it decreases current earnings, which undervalues the equity value.

Eberhart et al. (2004) findings suggest that firms with increasing R&D expenditure experience positive abnormal operating performance, which is congruous with the hypothesis that the market undervalues the R&D investments. They state that companies with noteworthy R&D expenditure may be mispriced in the market and its correction may take years.

Sougiannis and Yaekura (2001) assert that the reason why earnings forecasts for no or low R&D companies tend to be more precise is because analysts struggle to forecast the earnings of companies with high R&D expenditure. Consequently, since the R&D investment can take years to bear gains, the researchers suggest the utilization of longer forecasting horizons, otherwise firms with low R&D will have higher valuations.

Damodaran (1999) observes a significant impact of R&D expenses on the DCF and MBVM. In concrete, Schreiner and Spremann (2007) conclude that when R&D is capitalised instead of expensed, multiples based on accruals undervalue firms with significant R&D investment.

Contrarily to the aforementioned, Francis et al. (2000) realize that the RIVM has more explanatory when accounting treatments, as the R&D procedure, have an impact on value estimations. However, they find no difference in the RIVM accuracy of low and high R&D expenditure companies.

In conclusion, besides Francis et al. (2000), empirical evidence suggests that firms with high R&D investment have a huge disadvantage when being valued. Hence, the next section presents a correlated hypothesis.

2.6. Hypotheses Development

Demirakos, Strong et al. (2010) and Palepu et al. (2013) state that, theoretically, every single valuation model should produce the same value estimation. However, in practice, divergences in the models' implementation lead to different models yielding different valuations (Penman and Sougiannis, 1998; Francis et al., 2000; Lundholm and O'keefe, 2001). Therefore, this dissertation aims to contribute with empirical evidence about which valuation model performs best and the possible variances of the models' value estimations in large sample analysis. In specific, the performance of the four models will be linked to their valuation errors – difference between value estimation and share price four months after fiscal year-end – and a comparison of bias, accuracy and explainability will be conducted. Considering the previously presented literature, four hypotheses are developed.

As aforementioned, the comparison of FBVMs and MBVMs is limited. Courteau et al. (2006) realize that the valuation accuracy is higher for the RIVM than to a price to aggregated forecasted earnings multiple. Even when several horizon earnings forecasts are applied to the MBVM, the FBVMs derive a more accurate valuation (Liu et al, 2002). Considering that MBVMs are formulated on the methodology that the target company multiple will revert to the mean multiple of the comparable companies (Courteau et al., 2006), the MBVM estimation is vastly dependent on the comparable companies' choice (Alford, 1992). Hence, Boatsman and Baskin (1981) and Bhojraj and Lee (2002) argue that, whenever a suitable set of comparable companies cannot be ascertained or if the peers' share prices are mispriced, the MBVM valuations are unreliable. Moreover, firm-specific factors as long-term perpetual growth rate and risk are more probable to be correctly captured by a FBVM than a MBVM (Demirakos, Strong et al., 2010). In fact, Frankel and Lee (1998) and Lee and Swaminathan

(1999) find that the RIVM is a better stock return foreteller than various common multiples. Therefore, considering that MVBVs are conditioned on the peer companies and their respective bias and that FBVMs are contemplated as a more reliable valuation technique that better captures firm-specific information, the first hypothesis is conjectured:

H1: Flow-Based Valuation Models outperform in terms of bias, accuracy and explainability the Multiple-Based Valuation Model using 1-year ahead consensus forecasted earnings as a value driver.

Among the FBVMs, the DDM estimates the expected cash flows to be collected by the shareholders, however it does not absolutely correlate to the sources of value creation because dividends are sticky, in the sense that they are distributed without any link to earnings. Hence, dividends do not appropriately express the company's current circumstances. Oppositely, the DCF is less conservative because it appraises all the cash flows available to be paid to shareholders and solves the potential earnings management concerns (Damodaran, 2010). Although forecasting FCFE may be problematic and the DCF struggles in demonstrating the added value immediately (due to investments only collecting interests in the long run), this model materializes the impossible to alter cash movements and is not arbitrary like the DDM. Consequently, congruous with Francis et al. (2000), the DCF is presumed to have a better performance than the DDM, which prompts the second hypothesis:

H2: Discounted Cash Flow Model outperforms in terms of bias, accuracy and explainability the Dividend Discount Model.

Since the DCF is assessed as superior to the DDM, a comparison to the RIVM is conducted to determine which FBVM has the best performance. Even though both models are flow-based and derived from the same assumptions, the RIVM has an anchored component beyond the future flows, the BVE, which is an actual figure that does not require forecasting and that constitutes a high portion of the value estimation, which leads to the more uncertain TV having a lower proportion than in the other FBVMs (Francis et al., 2000). Moreover, although earnings forecasts are supposed to be more accurate and predictable than FCFE forecasts, Penman and Sougiannis (1998) state that the accrual aspect of earnings leads to the RIVM outperformance because it encompasses more business information than non-accrual measures. Even if some researchers proclaim that accrual figures empower earnings manipulation and thus more unreliable value estimations, Francis et al. (2000) assert a RIVM resistance to divergences in accounting practices and policies. Consistent with Healy (1984) and Nichols and Wahlen (2004), the RIVM overcomes other DCF weaknesses, as the timing and mismatch problem – solved by the accrual element – and the fact that investments are not contemplated as losses but rather as assets, in the short-term. Hence, analogous to Francis et al. (2000), the RIVM superiority is hypothesized:

H3: Residual Income Valuation Model outperforms in terms of bias, accuracy and explainability the Discounted Cash Flow Model.

To terminate, similar to Francis et al. (2000), the effect of R&D expenditure on the models' value estimates is examined. As previously argued, companies with sizeable R&D expenses demonstrate to have a limitation in their valuations, mostly because R&D investments understate accounting items (e.g., earnings and cash flows) before conducting to longer-term prosperity, which also generates difficulties in the forecasts' estimations (Eberhart et al., 2004). Francis et al. (2000) analyse the FBVMs performance for different samples of R&D investment. They argue that the RIVM is the most trustworthy model in all R&D contexts due to having the current BVE added to the flow component, whilst the other FBVMs are solely flow-based. Opposed to other researchers, they perceive no divergence on the FBVMs reliability at disparate R&D intensities, apart from a better explanatory power at high R&D expenditure.

The following hypothesis combines diverse past findings. Analogous to Francis et al. (2000), I conjecture that the RIVM is superior to the other FBVMs, since distortions in the book values of equity resultant of R&D investment are less severe than assumptions biases. However, contrary to these researchers and based on Sougiannis and Yaekura (2001) and Lie and Lie (2002), I infer that companies with no or low R&D expenditure have better value estimations than companies with high R&D intensity. Furthermore, the hypothesis covers not only the FBVMs, as Francis et al. (2000), but also the MBVM using one year ahead consensus forecasted earnings as a value driver, whereby is considered that selecting comparable companies based on the industry membership reflects equivalent R&D investments due to the industry competitiveness nature. Since companies with high R&D investment have a disadvantage in the equity value estimates produced by the valuation models, the final hypothesis is:

H4: Valuations for companies with zero or low R&D expenditure are better in terms of bias, accuracy and explainability than the valuations for companies with high R&D expenditure, whilst the models' performance ranking remains equal to the main analysis ranking.

3. LARGE SAMPLE ANALYSIS

In the following sections, the large sample utilized is delineated and the respective adjustments are illustrated, the procedures are described and the findings are scrutinized. Thereafter, the R&D influence on the models' performance is investigated and a sensitivity analysis is conducted. Subsequent to each analysis, the corresponding hypotheses are appraised.

3.1. Methodology

The three FBVMs and the selected MBVM, price to one year ahead consensus forecasted earnings, are applied to a large sample of U.S. public firms from diverse industries to assess the models' performance. The dataset has an observation period from 2005 to 2015 and the value estimations take place four months following the fiscal year-end (PRC4), as this period allows consensus forecasts and further relevant data to be incorporated into the stock prices.

Analogous to Francis et al. (2000), the analysis compares the models' value estimates with market prices. It is assumed that market prices are efficient, meaning that all the key information is perfectly reflected in the security prices (Timmermann and Granger; 2004, Courteau et al., 2006). The models' performance is evaluated on three levels:

1) Bias
2) Accuracy
3) Explainability

3.1.1. Data and Sample Specification

The initial dataset includes 37,106 observations with information from 6,108 public U.S. companies from numerous industries for the period 2005-2015, in which the data has been gathered from different data platforms. Consensus dividends and earnings forecasts are collected from Institutional Brokers' Estimation System (I/B/E/S), financial statement data – as BVE, CAPEX, common shares outstanding, current assets, current liabilities, D&A, NI, R&D

expenses, stock split adjustment factors and total assets – is collected from Compustat®, four months after fiscal year-end market prices and betas from Center for Research in Security Prices (CSRP) and risk-free rates from the U.S. Federal Reserve Bank.

In specific, I/B/E/S consensus forecasts are the mean forecasts calculated from all the available forecasts four months after fiscal year-end and beta is the annual stock beta computed by applying CSRP data on monthly firm-specific returns and on value-weighted return index for the entire market. All the financial statement data from Compustat® is stated in $ millions and market prices are supplied with a four months delay to guarantee that prices incorporate all the prior fiscal year information (Pazarzi, 2014). Furthermore, it is key to notice that while I/B/E/S and CSRP per share data are stock split and dividend adjusted, Compustat® per share data is not. Hence, all per share Compustat® information is adjusted.

Moreover, an initial inspection disclosed that extreme values are sometimes more than one hundred standard deviations off the mean. To prevent the findings from being misstated due to the outliers' impact, a winsorize level of 1% is applied. Hence, extreme values below the 1st percentile and above the 99th percentile are allocated a value equal to the value of the percentile (Boubaker and Nguye, 2014).

3.1.2. Sample Selection

The starting dataset comprises an extensive number of observations. Since this broader sample does not allow to accurately conduct the desirable analysis to test the hypotheses, the initial dataset is adjusted to fulfil the necessary conditions to conduct a proper analysis. Firstly, duplicates are eliminated.

As financial and utility companies are either from regulated industries or have special capital structures and accounting treatments, as Lie and Lie (2002) suggest, companies from these industries are removed from the dataset. The eliminated companies comprise all the firms with Standard Industrial Classification (SIC) code starting with "6" and "49".

The valuation models require several critical inputs to estimate the firm value. Considering that not all variables are available for all firm-years, missing data must be eliminated from the sample. In fact, there are several factors leading to missing observations, where the most common are the inexistence of analysts' forecasts for horizon t and the item not being obtainable from Compustat®. Francis et al. (2000) encourage that the dataset should only encompass companies with the full set of critical variables. Hence, for the observation to be included in the sample, it must contain the following variables every year:

- PRC4
- Beta (β)
- Book value of equity per share (BVEPS)
- 1-year and 2-year consensus forecasted earnings per share (EPS1 and EPS2)
- 1-year and 2-year consensus forecasted dividends per share (DPS1 and DPS2)
- 1-year and 2-year forecasted free cash flow to equity per share from valuation date (FCFEPS1 and FCFEPS2)

Value drivers must be positive, otherwise the computed value estimate will be negative. Following Courteau et al. (2006) suggestion, negative BVEPS and forecasted earnings are removed from the sample. This approach directly refutes Lee et al. (1999) method of replacing negative earnings by prior year total assets times average long-term ROA of 6%. By not employing the latter method, firms with negative earnings don't have an advantage over firms with zero or low earnings.

Additionally, since FCFE1 and FCFE2 aren't forecasted by I/B/E/S, I assume that analysts can flawlessly estimate free cash flows, thus the actual

FCFE of year one and two after the valuation date are utilized as forecasts. However, negative FCFEs must be deleted to ensure positive value estimates.

For the MBVM, each industry must have a satisfactory number of observations. To guarantee that FBVMs and MBVM analyses include the same number of observations, industry groups with less than 10 observations for each year are not considered. As Alford (1992), the industry groups are created in accordance with the two-digit SIC code.

Finally, companies with stock prices inferior to $1 are removed from the dataset because these companies have more fluctuating ratios and lower market liquidity (Frankel and Lee, 1998).

The final sample is displayed beneath.

Table 2 - Final Sample Selection

Adjustment Criteria	Number of Observations
Initial Sample	**37,106**
- Duplicates	(145)
	36,961
- Regulated industries (financial and utility)	(9,256)
	27,705
- Incomplete Dataset (prc4, β, BVEPS, EPS1, EPS2, DPS1, DPS2, FCFE1 and FCFE2)	(18,921)
	8,784
- Negative BVEPS	(262)
	8,522
- Negative EPS1 and EPS2	(628)
	7,894
- Negative FCFE1 and FCFE2	(3,823)
	4,071
- Industry Group with Less than 10 observations	(1,215)
	2,856
- Firms with stock price lower than $1	-
Final Sample	**2,856**

Table 2 depicts the adjustments made to the initial sample to ensure a uniform number of observations for all valuation models, which results in a higher degree of comparability for the following analyses.

To conclude, the final sample consists of 2,856 observations. This sample selection ensures a higher magnitude of comparability between the three FBVMS and the MBVM.

3.1.3. Model Specification

The following section specifies the models' inputs discussed in the literature review and their implementation issues are depicted.

3.1.3.1. MBVM Implementation Issues

Congruous with the findings of Beaver and Morse (1978), Kim and Ritter (1999) and Liu et al. (2002), the MBVM value driver utilized is the one-year ahead consensus forecasted earnings (EPS1) because it performs better than the other value drivers in terms of central tendency and dispersion. Notably, earnings are very illustrative of the firm's fundamentals and reflect the value creation, but since current earnings are more probable to fluctuate, be zero and often comprise transitory items, forecasted earnings are used to address these potential issues.

$$Value\ driver = \frac{Analysts'\,consensus\ forecast\ in\ year\ t+1}{Stock\ price\ 4\ months\ after\ fiscal\ year\ end} \qquad (3.1.)$$

As proposed by Alford (1992) and Baker and Ruback (1999), the comparable firms are chosen based on the first two-digit SIC code. Thereafter, following Beatty et al. (1999) and Liu et al. (2002) results, the benchmark multiple is computed by applying the harmonic mean, as this method yields the lowest pricing errors.

Furthermore, as Liu et al. (2002) suggest, the negative forecasted earnings are excluded from the sample to guarantee the absence of negative value drivers and, consequently, the absence of negative estimations that have the capability to mislead the results.

3.1.3.2. FBVMs Implementation Issues

The FBVMs introduced in the literature review are computed using a two-year horizon and a TV equation that assumes a perpetual constant growth rate (g) for the value driver from the second year onwards (Palepu et al., 2013). This time horizon is advocated by Frankel and Lee (1998) and Francis et al.

(2000) due to analysts usually only forecasting two years ahead. Implementing a longer horizon would result in a lower number of observations and a less statistical powered analysis.

An important implementation issue is the g utilized in the TV equation. Although some researchers advise a g equal to the inflation rate (Penman and Sougiannis, 1998), this analysis assumes a constant 4% perpetual growth rate, analogous with Francis et al. (2000).

The two-year forecasted flows need to be discounted to the valuation date. Since this dissertation is only considering the equity perspective (as mentioned in the chapter 2.2.), the discount rate employed is the cost of equity (r_e) and the CAPM is used to calculate it. However, the CAPM generates implementation issues that must be recognized.

Firstly, there is no consensus regarding which risk-free rate (r_f) should be employed. Numerous authors assert that the r_f should be the long-term T-bill or the intermediate treasury bond yield minus the historical premium on treasury bonds over T-bills (Ibbotson and Sinquefield, 1976; Francis et al., 2000). However, consistent with Penman and Sougiannis (1998), this dissertation assumes as r_f the three-year U.S. treasury bond yield at fiscal year-end for each year.

Secondly, the firm systematic risk, Beta (β), forms another issue. β demonstrates the volatility of a particular security compared to the all-inclusive market. Although negative β are excluded from the sample to refrain from negative r_e, as Fama and French (1997), Ross et al. (2009) and Hillier et al. (2010) illustrate, the industry median β is more precise than the firm's individual β when segregated by the two-digit SIC code. Therefore, when computing the CAPM, this analysis utilizes the industry median β to diminish the estimation errors.

Thirdly, the CAPM requires an assumption regarding the market risk premium (MRP). Harmonious with Penman and Sougiannis (1998), I assume a flat 6% MRP every year.

Generic to all models, the value drivers must be positive, otherwise the derived value estimate will be negative (Courteau et al, 2006). However, there are other implementation issues model specific. DCF model requires the expected free cash flows (FCF) for the following two years. Since none of the utilized databases produces FCF forecasts, I assume that analysts have the ability to perfectly forecast the FCF, meaning that the expected value one and two years ahead is equal to the actual value. Hence, I create lagged variables to approximate the variations in the working capital and net borrowing. Consistent with the equity perspective, the computation of free cash flow to equity per share is:

$$FCFE_1 = NI_1 + D\&A_1 - CAPEX_1 - \Delta WC_1 + \Delta Net\ Borrowings_1 \quad (3.2.)$$

$$FCFE_2 = NI_2 + D\&A_2 - CAPEX_2 - \Delta WC_2 + \Delta Net\ Borrowings_2 \quad (3.3.)$$

$$FCFEPS_1 = \frac{FCFE_1}{CSHO_1 * AJEX_1} \quad (3.4.)$$

$$FCFEPS_2 = \frac{FCFE_2}{CSHO_2 * AJEX_2} \quad (3.5.)$$

Where:

$FCFE_t$	Free Cash Flow to Equity of period t
NI_t	Net Income of period t
$D\&A_t$	Depreciation and Amortization expenses of period t
$CAPEX_t$	Capital expenditure of period t
ΔWC_t	Change in Working Capital during period t
$\Delta Net\ Borrowings_t$	Change in short and long-term debt minus cash during period t
$FCFEPS_t$	Free Cash Flow to Equity Per Share of period t
$CSHO_t$	Common shares outstanding of period t
$AJEX_t$	Adjustment factor for stock dividends and splits of period t

However, I acknowledge that the value estimate based on the DCF may not be entirely reliable because a very drastic assumption that is feasible to perfectly predict FCFs is needed, even though financial leverage may change over time (which will affect the FCFE) and items such as working capital are complex to identify (Damodaran, 2010).

Since no previous observations are stated for the first-year observations (i.e., 2005), the ΔWC_t and $\Delta Net\ Borrowings_t$ are set equal to the average of those changes. Furthermore, when no future figure is stated (i.e., 2015), the $FCFEPS$ is conjectured to grow at a perpetuity constant rate of 4% annually.

Moving on to RIVM, the model requests residual income (RI) forecasts. As for the FCF, the used databases don't forecast RI. Hence, to have RI future predictions, I assume that the Clean Surplus Relation (CSR) holds. By using the BVE, expected NI and expected dividends figures, the forecasted RI can be computed as in equation 2.11.

Regarding DDM, the main implementation issue is the company not paying dividends. The DDM can be computed using analysts' dividends consensus forecasts. However, if no dividends are expected to be paid, the DDM cannot produce intrinsic value estimations.

As Liu et al. (2002) propose, the dividend payout ratio, which is needful for RIVM, can be computed as dividends per share over NI per share and is assumed constant hereafter. If the ratio is below zero, the value is removed and if it is above one, the ratio is set equal to one.

3.1.3.3. Valuation Models Summary

A summary of all valuation models is displayed in table 3 to ensure an effortless comparison between the different models' procedures. For a detailed analysis of a specific valuation model, refer to the literature review.

Table 3 - Valuation Models Summary

Valuation Model	Formula
Dividend Discount Model (DDM)	$V_t^e = \frac{DPS1}{1+r_e} + \frac{DPS2}{(1+r_e)^2} + \frac{\frac{DPS2 * 1+g}{re-g}}{(1+r_e)^2}$
Discounted Cash Flow Model (DCF)	$V_t^e = \frac{FCFEPS1}{1+r_e} + \frac{FCFEPS2}{(1+r_e)^2} + \frac{\frac{FCFEPS2 * 1+g}{re-g}}{(1+r_e)^2}$
Residual Income Valuation Model (RIVM)	$V_t^e = BVEPS_t + \frac{RI1}{1+r_e} + \frac{RI2}{(1+r_e)^2} + \frac{\frac{RI2 * 1+g}{re-g}}{(1+r_e)^2}$ Where: $RI1 = EPS1 - BVEPS_t * r_e$ $RI2 = EPS2 - r_e * (BVEPS_t + (1 - div.payout) * EPS1)$
Multiple-Based Valuation Model using EPS1 (MBVM)	$V_t^e = EPS1 * \frac{1}{\frac{1}{n}\sum_{j=1}^{n}\frac{EPS1}{prc4}}$

Table 3 is a summary table of all the valuation models that are going to be used in the computation of different equity value estimates.

Where:

V_t^e	Firm's equity value at the valuation date
$DPS1$	Analysts' consensus forecast of dividend in year t+1 after the valuation date
$DPS2$	Analysts' consensus forecast of dividend in year t+2 after the valuation date
$FCFEPS1$	Free cash flow to equity per share in year t+1 after the valuation date
$FCFEPS2$	Free cash flow to equity per share in year t+2 after the valuation date
$BVEPS_t$	Book value of equity per share at the valuation date
$RI1$	Residual income per share in year t+1 after the valuation date
$RI2$	Residual income per share in year t+2 after the valuation date
$EPS1$	Analysts' consensus forecast of earnings per share in year t+1 after the valuation date
$EPS2$	Analysts' consensus forecast of earnings per share in year t+2 after the valuation date
$div.payout$	Dividend payout ratio
r_e	Cost of equity
g	Growth rate

Additionally, the cost of equity is calculated as follows:

$$r_e = r_f + \beta_{industry\ median} * MRP \qquad (3.6.)$$

r_f	Risk-free rate → three-year U.S. treasury bond yield
$\beta_{industry\ median}$	Industry median beta based on the first 2-digit SIC code
MRP	Market risk premium → 6%

3.1.4. Performance Measures of the Valuation Models

The relative performance of the valuation models is evaluated by the magnitude of the correspondence between the share price and the equity value estimates in terms of mean and median, as in Francis et al. (2000) and Courteau et al. (2001). To conduct this analysis, it is necessary to assume that markets are efficient because the models' estimates are compared to the market share price, where the latter is conjectured as the correct value of the company. Specifically, the best value estimates are the ones closest to the share price, so it is key to assume that markets are efficient and that prices reflect all the publicly available information accurately.

To analyse the value estimations in more detail, signed valuation errors (SVEs) and absolute prediction errors (APEs) are computed, both scaled by the share price. In fact, SVEs express the first assessment measure, bias. Since the positive and negative value estimates can cancel each other, this measure indicates whether the valuation model results in an under or overestimation of company's value, on average (Penman and Sougiannis, 1998). To assess how similar value estimations are to market prices, APEs are contemplated as they solely consider scaled absolute differences. Thus, APEs express the second assessment measure, accuracy.

$$SVE_i^M = \frac{V_t^e - PRC4_t}{PRC4_t} \quad (3.7.)$$

$$APE_i^M = \frac{|V_t^e - PRC4_t|}{PRC4_t} \quad (3.8.)$$

Where:

SVE_i^M	Price scaled signed valuation error of observation i using the model M = DDM, DCF, RIVM or MBVM
APE_i^M	Price scaled absolute prediction error of observation i using the model M = DDM, DCF, RIVM or MBVM
V_t^e	Firm's equity value estimated at the valuation date
$PRC4_t$	Share price 4 months after fiscal year-end

The statistical significance of the SVEs and APEs is evaluated by using t-tests for means and Wilcoxon signed-rank tests for medians (Martin and Bridgmon, 2012). In concrete, t-tests follow a parametric approach in which is assumed a normal population distribution, while the Wilcoxon signed-rank tests have a non-parametric approach that does not require such postulation (Anderson, 2017). Hence, to test the statistically significant difference from zero of the valuation errors using t-tests and Wilcoxon signed-rank tests, the hypotheses are as follows.

H_0: $Mean\ or\ Median\ Valuation\ Errors = 0$

H_1: $Mean\ or\ Median\ Valuation\ Errors \neq 0$

To compare between two models which one has the lowest valuation errors (and consequently performs best), a paired t-test is employed to compare the means and a two-sample Wilcoxon rank-sum is employed to compare the medians. Similar to the tests on the equality to zero, the paired t-test assumes a normal distribution where the variances are equivalent for both populations and the two-sample Wilcoxon rank-sum test does not require such assumption (Anderson, 2017). The hypotheses are:

$$H_0\text{: } Model\ 1\ Mean\ or\ Median\ Valuation\ Errors$$
$$= Model\ 2\ Mean\ or\ Median\ Valuation\ Errors$$

$$H_1\text{: } Model\ 1\ Mean\ or\ Median\ Valuation\ Errors$$
$$\neq Model\ 2\ Mean\ or\ Median\ Valuation\ Errors$$

To further assess the outcomes, ordinary least square (OLS) regressions are conducted to deduce how much of the share price variations are explained by the models' value estimates. Since OLS regressions assume that errors shouldn't have any patterns and, in practice, errors may have patterns, to ensure that the assumption isn't violated I use a robust variance-covariance matrix to mitigate the heteroscedasticity concerns. Thus, the third assessment measure is named explainability and its dispersion is shown by the regression's standard deviation (how much the values diverge from the mean). The hypotheses and regression methodology are:

H_0: $\beta_0 = \beta_1 = 0$
H_1: $\beta_0 \; and/or \; \beta_1 \neq 0$

$$Share\ price = \alpha + \beta * V_t^e + \varepsilon \quad (3.9.)$$

Where:

α	Constant
β	Regressor coefficient
V_t^e	Firm's equity value estimated at the valuation date
ε	Regression's residual

3.1.5. Descriptive Statistics of Key Variables

The sample adjustments comprised the dataset to 2,856 observations, which constitutes good balance between sufficiency and minimizing noise. As previously stated, extreme values of key variables are winsorized at 1% to deter the estimations from being misrepresented due to outliers.

The underneath table summarizes the descriptive statistics – number of observations, central tendency and dispersion – of key variables that will be used as inputs for the valuation models.

Table 4 - Descriptive Statistics of Key Variables

Statistics	PRC4	BVEPS	EPS1	EPS2	DPS1	DPS2	FCFE PS1	FCFE PS2	r_e
N	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856
Mean	47.85	14.90	2.82	3.20	0.67	0.70	4.33	3.88	9.00
Standard Deviation	34.08	11.35	2.13	2.35	0.81	0.84	4.32	3.89	2.31
Minimum	4.94	1.38	0.18	0.31	0.00	0.00	0.06	0.03	4.67
5th percentile	9.43	2.82	0.51	0.67	0.00	0.00	0.24	0.24	5.95
1st quartile	24.28	6.95	1.34	1.60	0.00	0.00	1.17	1.11	7.42
Median	40.14	11.78	2.31	2.60	0.42	0.44	2.85	2.50	8.53
3rd quartile	61.98	19.21	3.74	4.23	1.00	1.07	5.87	5.16	9.97
95th percentile	107.93	39.25	6.77	7.43	2.31	2.47	16.04	14.68	13.53
Maximum	202.54	61.87	12.30	13.66	3.88	3.96	44.68	43.33	17.94

Table 4 reports the key variables that will be used as inputs for the valuation models, with their number of observations, central tendency and dispersion. All variables are winsorized at 1% and have 2,856 observations, which guarantees high comparability for the analysis. The variables are, PRC4: Share Price 4-months after fiscal year-end; BVEPS: Book Value of Equity per share at the valuation date; EPS1: Analysts' consensus forecast of EPS in year t+1 after the valuation date; EPS2: Analysts' consensus forecast of EPS in year t+2 after the valuation date; DPS1: Analysts' consensus forecast of Dividend in year t+1 after the valuation date; DPS2: Analysts' consensus forecast of Dividend in year t+2 after the valuation date; FCFEPS1: Free Cash Flow to Equity per share in year t+1 after the valuation date; FCFEPS2: Free Cash Flow to Equity per share in year t+2 after the valuation date; r_e: Cost of Equity using CAPM (shown as %).

3.2. Empirical Findings

3.2.1. Descriptive Statistics of the Valuation Models Equity Value Estimates

Table 5 displays the descriptive statistics of the stock price four months after fiscal year-end and of the value estimates produced by the four models. The table demonstrates the number of observations, central tendency and dispersion measures, which provides an overview of all the sample companies. The results are winsorized at 1% to minimize the outliers' impact and to ensure consistency throughout the analysis.

The average and median stock prices of the sample companies are $47.85 and $40.14, respectively. These results signal a right-skewed distribution, where the same skewness applies to all the valuation models' outcomes.

Comparing the mean market stock prices to the mean estimates of the models, the MBVM appears to perform best, deviating solely 5.29% (+$2.53 deviation) from the stock prices. The RIVM deviates 30.62% (-$14.65), followed by the DDM with 61.92% deviation (+$29.63) and the DCF with 103.80% (-$49.67). The deficient performance of the DCF can as well be perceived from the exorbitant standard deviation.

However, when comparing the median stock prices to the median estimates of the models, the ranking is distinct. Based on medians, the RIVM has the best performance with a deviation of 4.81% (-$1.93) from the stock prices, while the DDM has the worst performance with an 80.67% (+$32.38) deviation. The MBVM is the second-best performer, deviating 7.03% (+$2.82) from the median stock price, followed by the DCF with a 36.15% (-$14.51) deviation. Despite the winsorizing procedure, differences in rankings may occur due to the presence of outliers that don't severely impact the analysis when considering medians.

The low value estimates of the DDM are generated due to the low DPS1 and DPS2 figures. Indeed, this model is predominantly influenced by the zero estimates of dividends, which results in a constant underestimation of value.

Nevertheless, no significant inferences can be made based on these outcomes. Therefore, the sample is going to be further scrutinized in terms of bias, accuracy and explainability.

Table 5 - Descriptive Statistics of Share Price and Value Estimates

Statistics	PRC4	DDM estimations	DCF estimations	RIVM estimations	MBVM estimations
N	2,856	2,856	2,856	2,856	2,856
Mean	47.85	18.22	97.52	62.50	45.32
Standard Deviation	34.08	28.77	115.88	66.48	33.29
Minimum	4.94	0.00	3.90	4.76	2.68
5th Percentile	9.43	0.00	6.87	8.41	8.15
1st Quartile	24.28	0.00	22.72	21.36	21.49
Median	40.14	7.76	54.65	42.07	37.32
3rd Quartile	61.98	23.28	122.02	77.65	60.85
95th Percentile	107.93	72.76	351.11	189.96	112.55
Maximum	202.54	173.92	593.75	397.79	172.13

Table 5 demonstrates the share price four months after the fiscal year-end (PRC4) and the value estimations of the different valuation models with their number of observations, central tendency and dispersion. All variables have 2,856 observations, which guarantees high comparability for the analysis. When comparing means, the MBVM performs best followed by the RIVM, but when comparing medians, the RIVM is the best followed by the MBVM. The DDM and DCF have poor performance, which for the DCF can as well be observed in the significant standard deviation. No meaningful inferences can be made based on these statistics; further analysis is necessary. All results are winsorized at 1%.

3.2.2. Valuation Errors

The beneath table 6 depicts the statistics of the APEs and SVEs for the valuation models being analysed, where the APEs depict the models' accuracy and the SVEs the models' bias. Each category of error is tested on the equality to zero using a t-test or a Wilcoxon signed-rank test. For this dissertation, the selected significance level is 5%.

At any significance level, the above-mentioned H_0 can be rejected for all valuation errors of all models for either the mean and median (p-value equal zero), except of the MBVM's mean SVE that has a p-value equal to 0.21, and thus cannot be rejected at any conventional significance level.

Regarding bias, when examining the mean, the MBVM SVE is statistically insignificant, meaning that this model doesn't tend to over- or underestimate the share price and therefore is the best performer model.

Followed by the RIVM, DDM and DCF, respectively, the latter is the most biased model with a 142% difference between the value estimate and the market share price. Considering medians – where medians are less dependent on outliers and don't require normality assumptions – the MBVM estimates are again the less biased with only a 2% difference from the share price. In contrast, the DDM performs the worst with a 79% divergence. Moreover, the RIVM appears again as the second less biased model (10% disparity from the market prices) and the DCF occupies the third place, deviating 39% from the share price.

In terms of accuracy, all the APEs are statistically significant, which indicates that all models are not entirely accurate. Still, for both the mean and the median, the MBVM is the most accurate model and is followed by the RIVM. However, for the mean, the DDM performs better than the DCF, while for the median the DCF has a better performance than the DDM. Although being the most accurate, the MBVM has an absolute 25% median deviation and a 34% mean deviation from the median and mean market prices, respectively, which is a reasonably pronounced divergence.

In general, the SVEs illustrate that the DDM and MBVM are negatively biased, meaning that the models tend to underestimate the firm value. Conversely, the DCF and RIVM SVEs are positively biased, so the models tend to overestimate firm value when compared to the market share price.

To sum up, the MBVM has the best performance in terms of bias and accuracy, followed by the RIVM. DDM and DCF demonstrate mixed evidence between them, but they are clearly worse than the RIVM and MBVM when analysing valuation errors.

Table 6 – Valuation Errors of the Four Models' Value Estimates

Model		DDM		DCF		RIVM		MBVM	
Valuation Error		***APE***	***SVE***	***APE***	***SVE***	***APE***	***SVE***	***APE***	***SVE***
N		2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856
Mean		0.77	-0.60	1.76	1.42	0.66	0.36	0.34	0.01
Standard Deviation		0.34	0.59	2.94	3.12	0.95	1.10	0.33	0.47
Median		0.83	-0.79	0.71	0.39	0.41	0.10	0.25	-0.02
Mean	t- value	120.20	-54.13	32.01	24.26	37.31	17.50	53.49	1.25
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21
Median	z-value	46.45	-37.91	46.29	23.76	46.29	13.13	46.29	-3.06
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 6 depicts the central tendency, dispersion and statistical significance of price scaled absolute prediction errors (APEs) and price scaled signed valuation errors (SVEs) for the four models. The significance is tested with t-tests for means and Wilcoxon sign-rank tests for medians. All valuation errors are statistically significant at 1% level besides the mean SVE for MBVM. The MBVM has the best bias and accuracy, followed by the RIVM. Mixed evidence appears for the DCF and DDM depending on the central tendency measure (mean or median).

The table 7 illustrates every paired test performed to examine the valuation errors of one model against the valuation errors of a disparate model. Since each p-value (showed between parentheses) is statistically significant at any significance level, the aforementioned null hypothesis can always be rejected. Hence, all the valuation errors of one model are different from the ones of a distinct model, therefore they must be further interpreted. In this paired comparison, the model with the smallest valuation errors has a relative superior performance to the comparison model.

The paired t-tests and two-sample Wilcoxon rank-sum tests imply that the MBVM is better in accuracy and bias than all the other methods, since its mean and median are always the smallest for both the APEs and SVEs. Succeeding in the ranking appears the RIVM, being more accurate and less biased than the DDM and DCF, either for the mean or median. Finally, mixed evidence occurs. The lower mean absolute and signed valuation errors of the DDM places the DCF as the worst performance model regarding accuracy and bias. However, when analysing the median, the DCF has a lower median absolute and signed valuation error than the DDM, so the DDM has the worst performance.

Table 7 - Paired Tests for the Valuation Errors of the Four Models' Value Estimates

Error	Absolute Prediction Errors				Signed Valuation Errors			
Stats	Mean	Mean Difference	Median	Median Difference	Mean	Mean Difference	Median	Median Difference
DDM DCF	0.77 1.76	-0.99 (0.00)	0.83 0.71	0.12 (0.00)	-0.60 1.42	-2.02 (0.00)	-0.79 0.39	-1.18 (0.00)
DCF RIVM	1.76 0.66	1.10 (0.00)	0.71 0.41	0.30 (0.00)	1.42 0.36	1.06 (0.00)	0.39 0.10	0.29 (0.00)
RIVM MBVM	0.66 0.34	0.32 (0.00)	0.41 0.25	0.16 (0.00)	0.36 0.01	0.35 (0.00)	0.10 -0.02	0.12 (0.00)
MBVM DDM	0.34 0.77	-0.43 (0.00)	0.25 0.83	-0.58 (0.00)	0.01 -0.60	0.61 (0.00)	-0.02 -0.79	-0.81 (0.00)
DDM RIVM	0.77 0.66	0.11 (0.00)	0.83 0.41	0.42 (0.00)	-0.60 0.36	-0.96 (0.00)	-0.79 0.10	-0.89 (0.00)
DCF MBVM	1.76 0.34	1.42 (0.00)	0.71 0.25	0.46 (0.00)	1.42 0.01	1.41 (0.00)	0.39 -0.02	0.41 (0.00)

Table 7 depicts the comparison of the valuation errors of one model with the valuation errors of other model by applying paired t-tests for means and two-sample Wilcoxon rank-sum tests for medians. P-values are depicted between parentheses. All differences are statistically significant at 1% level. The MBVM has the best bias and accuracy, followed by the RIVM. Mixed evidence appears for the DCF and DDM depending on the central tendency measure (mean or median).

3.2.3. OLS Regression Analyses

The last performance measure scrutinized is the explainability of the value estimations produced by the different valuation models. By employing OLS regressions, the valuation models' explanatory power is evaluated. Hence, four univariate OLS regressions of PRC4 (dependent variable) on the four different value estimates (independent variable) and a multivariate regression of PRC4 on equity value estimates of the MBVM and RIVM have been computed.

Table 8 panel A depicts the four univariate OLS regressions. By conducting a white test for each model, the existence of heteroscedasticity in the four models is determined with p-values of 0.00, hence robust standard errors are applied to mitigate this concern.

According to Woolridge (2012), the R^2 is an indicator of explainability, thus its interpretation is critical to assess the explanatory power of each valuation model. The R^2 is the biggest for the MBVM, followed by the RIVM, DCF and DDM, respectively. Therefore, the MBVM is the model with highest explanatory power, where its equity value estimates explain 54% of the stock price's variability. While the RIVM explains a little bit less with 33%, the explanatory power of the DCF and DDM value estimations is very low, explaining 11 and 7% of the stock price, respectively. These findings emphasize the outperformance of the MBVM over the three flow-based valuation models, whilst the RIVM has the best performance among the FBVMs.

Moreover, the constants capture all the distortions that are not contemplated by the models. In fact, the constants are very high in every regression, thus other determinants not reflected in the valuation models influence significantly the share price. Furthermore, a positive significant coefficient in all regressions underlines an underestimation of value by the four models. With the largest coefficient, the MBVM has the highest impact as for every unit increase in the valuation implied by the model, the share price increases by $0.76. The impact of the other models is less than half of the MBVM impact, with the DDM only having a $0.10 increase for every one unit increase in the value estimation. It is possible to conclude that none of the four models is perfectly correlated to PRC4, otherwise the coefficients would equal one. It is important to refer that all constants and coefficients are statistically significant at any significance level, therefore they are statistically different from zero.

Additionally, the two models with best performance, the MBVM and RIVM, are juxtaposed in a multivariate regression. Table 8 panel B depicts the results of the PRC4 regression on the explanatory variables MBVM and RIVM. The inclusion of the RIVM value estimates solely adds 1% to the R^2 of the univariate regression including the MBVM alone. Thus, the RIVM only captures a minuscule volume of supplementary information when compared to the MBVM.

Table 8 – Univariate and Multivariate Regression Results of Stock Prices (PRC4) on Equity Value Estimates

Panel A: Univariate Regressions of Stock Price on Equity Value Estimates [1]

Valuation Model	OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
DDM	β	0.31	0.03	12.17	0.00	0.26	0.36
	Constant	42.23	0.73	57.73	0.00	40.80	43.67
DCF	β	0.10	0.01	13.56	0.00	0.08	0.11
	Constant	38.24	0.74	51.67	0.00	36.78	39.69
RIVM	β	0.29	0.02	19.18	0.00	0.26	0.32
	Constant	29.58	0.84	35.15	0.00	27.93	31.23
MBVM	β	0.76	0.02	35.35	0.00	0.71	0.80
	Constant	13.62	0.88	15.50	0.00	11.90	15.35

	DDM	DCF	RIVM	MBVM
Obs.	2,856	2,856	2,856	2,856
Prob > F	0.00	0.00	0.00	0.00
R^2	0.07	0.11	0.33	0.54

Panel B: Multivariate Regression of Stock Price on Equity Value Estimates of MBVM and RIVM [2]

OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
β_{MBVM}	0.67	0.03	26.55	0.00	0.62	0.72
β_{RIVM}	0.06	0.01	5.92	0.00	0.04	0.08
Constant	13.62	0.86	15.79	0.00	11.93	15.31

Obs.	2,856
Prob > F	0.00
R^2	0.55

[1]*Panel A depicts the OLS regression results of univariate regressions Share Price = $\alpha + \beta V^{M} + \varepsilon$, where a is the constant, V^{M} is the value estimate using the model M = DDM, DCF, RIVM, or MBVM and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. The ascendent order of explanatory power of the regressions is DDM, DCF, RIVM and MBVM.*

[2]*Panel B depicts the OLS regression results of multivariate regression Share Price = $\alpha + \beta\, V^{MBVM} + \beta\, V^{RIVM} + \varepsilon$, where a is the constant, V^{MBVM} is the value estimate using the MBVM, V^{RIVM} is the value estimate using the RIVM and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. Including V^{RIVM} on the multivariate regression solely adds 1% to the R^2 of the univariate regression including only the MBVM.*

3.2.4. Summary of Performance Measures Findings

Table 9 - Summary of the Three Performance Measures of the Valuation Models

Panel A – Summary of the Valuation Errors of the Four Models' Value Estimates [1]

Valuation Error	DDM		DCF		RIVM		MBVM	
	APE	***SVE***	***APE***	***SVE***	***APE***	***SVE***	***APE***	***SVE***
N	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856
Mean	0.77 (0.00)	-0.60 (0.00)	1.76 (0.00)	1.42 (0.00)	0.66 (0.00)	0.36 (0.00)	0.34 (0.00)	0.01 (0.21)
Median	0.83 (0.00)	-0.79 (0.00)	0.71 (0.00)	0.39 (0.00)	0.41 (0.00)	0.10 (0.00)	0.25 (0.00)	-0.02 (0.00)

Panel B – Summary of the Univariate Regression Results of Stock Prices on Equity Value Estimates [2]

Valuation Model	DDM	DCF	RIVM	MBVM
N	2,856	2,856	2,856	2,856
R^2	0.07 (0.00)	0.11 (0.00)	0.33 (0.00)	0.54 (0.00)
β	0,31 (0.00)	0.10 (0.00)	0.29 (0.00)	0.76 (0.00)
Constant	42.23 (0.00)	38.24 (0.00)	29.58 (0.00)	13.62 (0.00)

[1]*Panel A depicts the central tendency and statistical significance of the price scaled absolute prediction errors (APEs) and price scaled signed valuation errors (SVEs) for the four models. The significance is tested with t-tests for means and Wilcoxon sign-rank tests for medians. P-values are presented between parentheses. All valuation errors are statistically significant at 1% level besides the mean SVE for MBVM. The MBVM has the best bias and accuracy, followed by the RIVM. Mixed evidence appears for the DCF and DDM depending on the central tendency measure (mean or median).*

[2]*Panel B depicts OLS regression results of univariate regression Share Price = $\alpha + \beta V^M + \varepsilon$, where a is the constant, V^M is the value estimate using the model M = DDM, DCF, RIVM, or MBVM and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values presented between parentheses show the significance. The ascendent order of explanatory power of the regressions is DDM, DCF, RIVM and MBVM.*

3.2.5. Results

The hypotheses formulated in the last chapter of the literature review will be individually scrutinized in this section. All the following regressions yield an explanatory contribution as the Prob > F is always 0.00.

3.2.5.1. Hypothesis 1 Assessment

H1: Flow-Based Valuation Models outperform in terms of bias, accuracy and explainability the Multiple-Based Valuation Model using 1-year ahead consensus forecasted earnings as value driver.

As presented in table 9 panel A, the MBVM has the lowest mean and median APEs and SVEs. In fact, the mean SVE of the MBVM is statistically insignificant, meaning that the model is not biased when examining the mean. Therefore, the MBVM using 1-year ahead consensus forecasted earnings as value driver outperforms the three flow-based valuation models in terms of bias and accuracy.

Table 10 depicts the multivariate regression of PRC4 as a dependent variable on DDM, DCF and RIVM value estimates as regressors. Every coefficient is statistically significant at any common significance level (p-values equal 0.00), except the DDM coefficient that is statistically insignificant (p-value equal to 0.88). This insignificance outlines that when regressing the three FBVMs together, the DCF does not incorporate any relevant information to the combined model.

The R^2 of this multivariate FBVMs regression is 0.35, indicating that 35% of the share price variances are explained by the equity value estimates of the three FBVMs combined. However, the univariate regression of PRC4 on the MBVM value estimates presented in table 9 panel B has an R^2 of 54%. This indicates that the MBVM alone has a larger explanatory power than the three flow-based models combined.

Table 10 - Multivariate Regression of PRC4 on Equity Value Estimations of DDM, DCF and RIVM

OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
β_{DDM}	-0.27	0.04	-7.50	0.00	-0.34	-0.20
β_{DCF}	-0.00	0.01	-0.15	0.88	-0.02	0.01
β_{RIVM}	0.37	0.02	16.80	0.00	0.33	0.41
Constant	29.62	0.75	39.38	0.00	28.14	31.09
Obs.	2,856					
Prob > F	0.00					
R^2	0.35					

Table 10 depicts the OLS regression results of multivariate regression Share Price = $\alpha + \beta$ $V^{DDM} + \beta$ $V^{DCF} + \beta$ $V^{RIVM} + \varepsilon$, where a is the constant, V^{DDM} is the value estimate using the DDM, V^{DCF} is the value estimate using the DCF, V^{RIVM} is the value estimate using the RIVM and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. Combining V^{DDM}, V^{DCF} and *V^{RIVM} on the multivariate regression yields an R^2 of 0.35, meaning that all FBVMs combined explain 35% of the variability of the share price 4 months after fiscal year-end.*

Moreover, by taking into consideration the four univariate regression coefficients (table 9 panel B), the MBVM has the highest one, 0.76, meaning that a 1% increase in the valuation implied by the model results in a 0.76% increase in the stock price.

Considering every univariate regression on table 9 panel B, where the MBVM regression has the highest R^2 and coefficient of them all, and the above-stated multivariate regression, it is feasible to conclude that the MBVM using 1-year ahead consensus forecasted earnings as a value driver is superior to the three flow-based valuation models individually and combined in terms of explainability.

The MBVM superiority in all of the performance measures may be attributable to the implementation issues and assumptions of the FBVMs creating bigger valuation errors than the MBVM dependence on the comparable companies. Additionally, the fewer assumptions required and the usage of actual share prices as direct input of the multiple-model (which has the capability of capturing the market sentiment) might result in valuations closer to the observed share prices. Oppositely, the FBVMs don't truly capture the current mood of the market, as stated by Schreiner and Spremann (2007). Thus, these findings contradict Frankel and Lee (1998), Courteau et al. (2006) and Imam et al. (2013) as the researchers proclaim that the MBVM performs worse than the FBVMs.

In conclusion, from the four valuation models employed in this dissertation, the multiple-based valuation model using 1-year ahead consensus forecasted earnings as a value driver is the best model regarding bias, accuracy and explainability.

Hypothesis 1 is rejected.

3.2.5.2. Hypothesis 2 Assessment

H2: Discounted Cash Flow Model outperforms in terms of bias, accuracy and explainability the Dividend Discount Model

As table 9 panel A depicts, when considering the mean, the DDM has the lowest APEs and SVEs, however when examining the median, the previous errors are smallest for the DCF. By analysing the central tendency measures, the findings provide mixed evidence regarding which model performs best in terms of bias and accuracy.

Although the mean is the value that diminishes the prediction error of any observation in the dataset, when the data is skewed it is remarkably susceptible to the outliers' impact. Therefore, since the data is right-skewed, as shown in the descriptive statistics of section 3.2.1., the mean loses its potential to generate the best central location, whilst the median can preserve its estimation as it isn't greatly affected by outliers and skewed values. Hence, by considering the most precise measure, the median, the DCF is less biased and more accurate than the DDM.

Table 11 illustrates the multivariate regression of PRC4 on the DDM and DCF value estimations as independent variables. The statistically significant R^2 of this regression is 0.13, meaning that 13% of the share price variability is explained by the combined value estimations derived from the DDM and DCF. Moreover, the univariate regressions of PRC4 on the DDM and DCF value estimations individually present an R^2 of 0.07 and 0.11, respectively. Such outcomes indicate that adding the DDM information to the DCF value estimations solely captures approximately 2% of additional information, while on the contrary scenario of adding the DCF estimations to the DDM, the explanatory power of the model almost doubles.

At any significance level, all the coefficients are statistically significant. The DCF coefficient is lower than the 0.16 DDM coefficient, emphasizing that a 1% increase in the DDM value estimate is connected to a 0.16% increase in the stock price. Although the DDM value estimation is more linked to the actual share price than the DCF estimates, the latter comprises more explanatory power.

Table 11 - Multivariate Regression of PRC4 on Equity Value Estimations of DDM and DCF

OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
β_{DDM}	0.16	0.03	5.57	0.00	0.10	0.22
β_{DCF}	0.08	0.01	9.75	0.00	0.06	0.10
Constant	37.09	0.76	49.07	0.00	35.61	38.57
Obs.	2,856					
Prob > F	0.00					
R^2	0.13					

Table 11 depicts the OLS regression results of multivariate regression Share Price = $\alpha + \beta\ V^{DDM} + \beta\ V^{DCF} + \varepsilon$, where a is the constant, V^{DDM} is the value estimate using the DDM, V^{DCF} is the value estimate using the DCF and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. Combining V^{DDM} and V^{DCF} on the multivariate regression yields an R^2 of 0.13, meaning that V^{DDM} and V^{DCF} combined explain 13% of the variability of the share price 4 months after fiscal year-end. Hence, including V^{DDM} to the V^{DCF} univariate regression only captures 2% of additional information.

Almost all analyses culminate in the conclusion that the DCF outperforms in terms of bias, accuracy and explainability the DDM, which is consistent with the Francis et al. (2000) findings. The theoretical rationale that supports this verdict is delineated in section 2.6. Nevertheless, as a consequence of the closeness of the results, a more detailed analysis between the DCF and

DDM performance would be advisable, which grants space for future researchers to proceed.

Hypothesis 2 cannot be rejected.

3.2.5.3. Hypothesis 3 Assessment

H3: Residual Income Valuation Model outperforms in terms of bias, accuracy and explainability the Discounted Cash Flow Model.

Table 9 panel A illustrates that the RIVM value estimates has lower mean and median APEs and SVEs than the DCF value estimation. Hence, the RIVM outperforms the DCF in bias and accuracy.

Table 12 illustrates the multivariate regression of PRC4 on DCF and RIVM value estimates together. The RIVM coefficient is statistically significant at any significance level, however the DCF coefficient is statistically insignificant with a 0.43 p-value. The DCF coefficient insignificance denotes that the DCF does not comprise any additional information to the RIVM. This result is also supported by the 0.33 multivariate regression R^2. Since this explanatory power is exactly equal to the explanatory power of the univariate regression of PRC4 on the RIVM, the RIVM value estimate alone captures all the information of the multivariate regression of the PRC4 on the combined DCF and RIVM value estimations. Therefore, it is viable to conjecture that the RIVM outperforms the DCF in terms of explainability.

Furthermore, regarding the univariate regression coefficients (table 9 panel B), the 0.29 RIVM coefficient is higher than the DCF coefficient, which illustrates that a 1% increase in the RIVM valuation leads to a bigger increase in the market stock price than the DCF valuation.

Table 12 - Multivariate Regression of PRC4 on Equity Value Estimations of DCF and RIVM

OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
β_{DCF}	-0.01	0.01	-0.79	0.43	-0.02	0.01
β_{RIVM}	0.30	0.02	15.37	0.00	0.26	0.34
Constant	29.77	0.81	36.85	0.00	28.18	31.35
Obs.	2,856					
Prob > F	0.00					
R^2	0.33					

Table 12 depicts the OLS regression results of multivariate regression Share Price = $\alpha + \beta\ V^{DCF} + \beta\ V^{RIVM} + \varepsilon$, where a is the constant, V^{DCF} is the value estimate using the DCF, V^{RIVM} is the value estimate using the RIVM and ε is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. The p-value of the V^{DCF} coefficient is statistically insignificant at 5% level, meaning that the DCF inclusion does not carry any additional information. Combining V^{DCF} and V^{RIVM} on the multivariate regression yields an R^2 of 0.33, equal to the R^2 of V^{RIVM} univariate regression.

To conclude, all the tests infer that the RIVM outperforms the DCF in terms of bias, accuracy and explainability. These findings are congruous to Francis et al. (2000) results but contradict the Courteau et al. (2001) opinion that both models perform equivalently. As discussed in section 2.6., the RIVM superiority derives from the model specification because it uses the current BVE available in the balance sheet as an input, which causes the model to be less dependent on the more unreliable TV. Moreover, the DCF only employs forecasted items and contemplates investments negatively in the short-term.

Hypothesis 3 cannot be rejected.

3.2.6. Research and Development (R&D) Expenditure on the Valuation Models

In this sub-section, the R&D subsamples are identified to enhance the analysis concerning the influence of R&D. The suitability of the different valuation models for distinct magnitudes of R&D expenditure is analysed for bias, accuracy and explainability before testing the hypothesis.

3.2.6.1. Selection of the R&D Subsamples

Analogous to Francis et al. (2000), two R&D subsamples are established, one for companies with zero or low R&D expenditure and another for companies with high R&D expenditure. In concrete, based on the Compustat® ratio of R&D expenditure over beginning of the year total assets, the 2,856 observations from the final sample are divided into quartiles, where the first quartile (lowest 25% observations) represents the low R&D subsample and the fourth quartile (highest 25% observations) the high R&D subsample. This approach is influenced by Francis et al. (2000) but differs since the researchers characterize the low R&D subsample as the firms with no or immaterial R&D investments, comprising 48% of their total sample, and the top quartile of highest R&D investment as the high R&D subsample. Their approach compares a dissimilar number of observations between subsamples, while this dissertation approach compares an equal number of observations for both subsamples, which generates better comparability between subsamples and greater confidence in the reliability of the findings. Observations without R&D information are removed.

Table 13 - Sample Adjustments for the R&D Analysis

Adjustment	Number of Observations
Final Sample	2,856
Removal of Blank Observations for R&D	-24
Total Observations for the Subsample	2,832
1st Quartile (Lowest 25% R&D Expenditure)	**708**
4th Quartile (Highest 25% R&D Expenditure)	**708**

Table 13 demonstrates the two R&D subsamples created for the analysis of the impact of R&D expenditure on the models' value estimations. After removing observations without R&D information, based on Compustat® ratio of R&D expenditure over beginning of the year total assets, the final sample is divided into quartiles, where the first quartile (lowest 25% observations) represents the low R&D subsample and the fourth quartile (highest 25% observations) the high R&D subsample.

3.2.6.2. Descriptive Statistics of the R&D Subsamples

Companies from the low R&D subsample spend on average 2.95% of their total assets on R&D, whilst the companies from the high R&D subsample spend 43.67% (almost 15 times more). For both samples, the share price four months after fiscal year-end and all the models' value estimates depict a right-skewed distribution. All values presented in table 14 are winsorized at 1% level to minimize the outliers' impact.

The $47.68 mean PRC4 for the high R&D subsample is closest to the mean PRC4 of the complete sample than the $45.35 for the low R&D subsample. Considering both measures of central tendency, the high R&D subsample has a higher share price, which contradicts Schreiner and Spremann (2007), who argue that a high R&D expenditure company is penalised with a lower value of equity.

In both subsamples, the RIVM and DCF valuations tend to overestimate value (the latter in a greater extent), while the DDM and MBVM underestimate value. In the low R&D subsample, mixed evidence is depicted. Considering the mean, the MBVM estimates are closer to PRC4, followed by the RIVM, DDM and DCF, respectively. However, when analysing the median, the RIVM outperforms the others, followed by the MBVM, DCF and DDM, respectively. For the high R&D subsample, the MBVM produces the closest to PRC4 value estimations and the RIVM appears right after. Regarding the DDM and DCF on the high R&D subsample, mixed evidence emerges depending on the central tendency measure. For both subsamples, in line with the main analysis, the DCF has the largest variation, illustrated by the standard deviation.

Overall, based on the descriptive statistics, the main analysis performance ranking is only reflected in the high R&D subsample. Nevertheless, no inferences can be taken from these findings. Hence, the subsamples are further analysed for bias, accuracy and explainability.

Table 14 - Descriptive Statistics of Share Price and Value Estimates for the Low and High R&D Expenditure Subsamples

	Low R&D Expenditure Subsample					High R&D Expenditure Subsample				
	PRC4	**DDM**	**DCF**	**RIVM**	**MBVM**	**PRC4**	**DDM**	**DCF**	**RIVM**	**MBVM**
N	708	708	708	708	708	708	708	708	708	708
Mean	45.34	16.13	78.92	55.21	42.13	47.68	22.33	126.27	72.09	46.65
Standard Deviation	38.25	26.25	99.07	65.27	35.90	27.99	36.20	140.16	74.15	28.75
Minimum	4.94	0.00	3.90	4.76	2.68	4.94	0.00	3.90	5.00	2.68
5th Percentile	7.16	0.00	5.36	6.89	5.83	11.25	0.00	9.63	10.04	10.28
1st Quartile	20.18	0.00	16.99	17.15	17.17	28.24	0.00	30.52	26.16	25.25
Median	35.42	6.13	43.10	32.58	32.10	42.57	8.18	73.90	50.42	40.69
3rd Quartile	57.05	18.47	97.96	67.14	54.51	60.97	28.54	161.63	86.15	62.64
95th Percentile	121.10	73.13	279.42	182.55	123.24	99.36	96.18	453.95	224.95	99.18
Maximum	202.54	173.92	593.75	397.79	172.13	202.54	173.92	593.75	397.79	172.13
Average R&D spending	2.95%					43.67%				

Table 14 reports the share price four months after the fiscal year- end (PRC4) and the value estimates of the different valuation models with their number of observations, central tendency and dispersion for the low and high R&D expenditure subsamples. The subsamples' average R&D spending is also depicted. All variables have 708 observations, which guarantees high comparability for the analysis. In both subsamples, the RIVM and DCF overestimate value, while the DDM and MBVM underestimate. The low R&D subsample presents mixed evidence. Considering the mean, the MBVM estimates are closer to PRC4, followed by the RIVM, DDM and DCF, respectively. Considering the median, the RIVM estimates are closer to PRC4, followed by the MBVM, DCF and DDM, respectively. For the high R&D subsample, the MBVM produces the closest to PRC4 value estimations, followed by the RIVM. Mixed evidence emerges for DDM and DCF depending on the central tendency measure. All values are winsorized at 1%.

3.2.6.3. R&D Subsamples Valuation Errors

Table 15 depicts the valuation errors for the low and high R&D expenditure subsamples, along with the valuation errors difference of the low to the high R&D subsample. T-tests, Wilcoxon sign-rank tests, paired t-test and two-sample Wilcoxon rank-sum tests are conducted to analyse the significance of the results (p-values presented between parentheses). The chosen significance level for the analysis is 5%. All the coefficient interpretations assume the coefficient significance unless stated otherwise.

For both subsamples, the MBVM has the lowest mean and median APEs and SVEs, followed by the RIVM, meaning these models perform best in bias and accuracy. In particular, the SVEs generated by the MBVM in the low R&D subsample are statistically insignificant at a 5% level, suggesting that this model in this subsample is not biased. The same happens to the median APEs of the MBVM in the high R&D subsample, which indicates that the median APEs are statistically equal to zero. For both subsamples, the DDM has a better bias and accuracy performance than the DCF when considering the mean, however the order inverts when considering the median. The same happens in the main analysis results. Considering that the subsamples price and valuations are right-skewed, the mean is influenced by the outliers' impact, while the median is not. Thus, by analysing the median, the DCF is less biased and more accurate than the DDM. Hence, the performance ranking – firstly MBVM, followed by RIVM, DCF and DDM, respectively – is congruous with the findings of the main analysis.

By performing paired tests of the valuation errors on both R&D subsamples, the negative difference between the valuation errors of the samples demonstrates a bias and accuracy superiority of the low R&D subsample for the DDM, DCF and RIVM. Surprisingly, the MBVM is more accurate in the high R&D subsample and the signed valuation errors differences are statistically insignificant at 5%, indicating that there is no difference between the subsamples' bias for the MBVM.

Based on these findings, the FBVMs seem to be less biased and more accurate in the low R&D subsample, while the MBVM has an equivalent bias in both samples and better accuracy in the high R&D subsample. Hence, solely for the FBVMs, companies with zero or low R&D expenses generate less biased and more accurate valuations than companies with high R&D expenses. This contradicts Francis et al. (2000) findings that no differences in bias and accuracy result from the low and high R&D expenditure subsamples. Analogous to the researchers, I deduce the RIVM superiority over the other FBVMs, whilst I also deduce the MBVM surpassing performance over all FBVMs in terms of bias and accuracy in both subsamples.

Table 15 - Models' Valuation Errors for the R&D Subsamples and Differences of Subsamples' Valuation Errors

Subsample		**Low R&D Subsample**		**High R&D Subsample**		**Difference Subsamples**	
Error		**APE**	**SVE**	**APE**	**SVE**	**APE**	**SVE**
DDM	**Mean**	0.76 (0.00)	-0.63 (0.00)	0.80 (0.00)	-0.54 (0.00)	-0.04 (0.02)	-0.09 (0.00)
	Median	0.84 (0.00)	-0.79 (0.00)	0.88 (0.00)	-0.80 (0.00)	-0.04 (0.02)	0.01 (0.57)
DCF	**Mean**	1.62 (0.00)	1.23 (0.00)	2.21 (0.00)	1.96 (0.00)	-0.59 (0.00)	-0.73 (0.00)
	Median	0.71 (0.00)	0.28 (0.00)	0.85 (0.00)	0.78 (0.00)	-0.14 (0.00)	-0.50 (0.00)
RIVM	**Mean**	0.62 (0.00)	0.28 (0.00)	0.78 (0.00)	0.53 (0.00)	-0.16 (0.00)	-0.25 (0.00)
	Median	0.41 (0.00)	0.04 (0.00)	0.45 (0.00)	0.22 (0.00)	-0.04 (0.01)	-0.18 (0.00)
MBVM	**Mean**	0.37 (0.00)	0.02 (0.43)	0.31 (0.00)	0.04 (0.01)	0.06 (0.00)	-0.02 (0.29)
	Median	0.28 (0.00)	-0.05 (0.07)	0.23 (0.00)	0.03 (0.15)	0.05 (0.00)	-0.08 (0.10)

Table 15 reports the mean and median price scaled absolute prediction errors (APEs) and price scaled signed valuation errors (SVEs) of the R&D subsamples and the mean and median differences of the subsamples' valuation errors. The significance is tested with t-tests for mean, Wilcoxon sign-rank test for medians, paired t-tests for mean differences and two-sample Wilcoxon sum-rank test for median differences. P-values are presented between parentheses. For both subsamples, the MBVM performs best in bias and accuracy, followed by RIVM. When analysing the mean, for both subsamples the DDM performs best in bias and accuracy than DCF. When analysing the median, for both subsamples the DCF performs best in bias and accuracy than DDM. Considering that subsamples are right-skewed, the median ranking should be considered, therefore the DCF is superior to the DDM. The FBVMs perform best in bias and accuracy in the low R&D subsample, while the MBVM performs best in accuracy in the high R&D subsample and has equal bias in both subsamples (proved by a statistical insignificant difference for mean and median SVEs).

3.2.6.4. OLS Regression Analyses of the R&D Subsamples

The subsamples' explainability are tested by employing univariate OLS regressions of the stock price on equity value estimations, where all regressions yield an explanatory contribution. The R^2 of all FBVMs is highest in the low R&D subsample, except the DCF that has equal explanatory power in both samples. In contrast, the MBVM has the highest explanatory power on the high R&D subsample. This evidence is consistent with the previous analysis of the subsamples but contradicts Francis et al. (2000) results, since the authors find that the FBVMs have the highest explainability in the high R&D expenditure subsample.

For both subsamples, and as in the main sample, the MBVM has the highest explainability, followed by the RIVM, DCF and DDM, respectively. Comparing to the main analysis, the low R&D subsample provides more explainability to all the FBVMs, which is likely due to having fewer observations of probable more similar companies. However, in the high R&D subsample, the evidence is different. Although having a more uniform dataset, the DDM and RIVM have less explanatory power in this subsample than in the main sample, while the DCF has 1% more. Hence, the FBVMs explainability performance is enhanced in companies with zero or low R&D expenditure and diminished in companies with higher R&D expenditure (apart from the DCF that in both subsamples has better explanatory power). Regarding the MBVM, comparing to the original sample, the low and high R&D subsamples yield lower and equal explainability for the model, respectively.

All constants and coefficients are statistically significant at any significance level. For every model, the coefficient is higher in the low R&D subsample than in the other subsample or the main analysis, suggesting that the models' value estimates for companies with no or low R&D investment are more correlated with the actual share price. In contrast, all the coefficients are lower in the high R&D subsample than in the main sample, which indicates that valuations for companies with high R&D investments are less correlated with the actual share price. Regarding the constants, compared to the main sample, they are lower for the low R&D subsample and higher for the high R&D subsample, meaning that there are fewer and more distortions in each analysis, respectively.

To conclude, FBVMs have the highest explanatory power in the low R&D subsample and the MBVM has the highest explanatory power in the high R&D subsample. The valuation models' performance ranking is not altered in both subsamples and is analogous to the main analysis. Hence, the ascendant order of explanatory power of the models is DDM, DCF, RIVM and MBVM.

Table 16 - Univariate Regressions of Stock Price on Equity Value Estimates for the Low and High R&D Subsamples

Panel A: Univariate Regressions of Stock Price on Equity Value Estimates for the Low R&D Subsample [1]

Valuation Model	OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
DDM	β	0.46	0.07	7.09	0.00	0.34	0.59
	Constant	37.85	1.61	23.49	0.00	34.68	41.01
DCF	β	0.13	0.02	6.29	0.00	0.09	0.18
	Constant	34.79	1.73	20.17	0.00	31.41	38.18
RIVM	β	0.37	0.32	11.52	0.00	0.30	0.43
	Constant	25.20	1.59	15.85	0.00	22.08	28.32
MBVM	β	0.76	0.05	16.64	0.00	0.67	0.85
	Constant	13.24	1.77	7.49	0.00	9.76	16.71

	DDM	DCF	RIVM	MBVM
Obs.	708	708	708	708
Prob > F	0.00	0.00	0.00	0.00
R^2	0.10	0.12	0.39	0.51

Panel B: Univariate Regressions of Stock Price on Equity Value Estimates for the High R&D Subsample [2]

Valuation Model	OLS Coefficients		Robust Standard Errors	t-Value	p-Value	95% Confidence Level	
DDM	β	0.18	0.03	5.69	0.00	0.12	0.24
	Constant	43.77	1.23	35.49	0.00	41.35	46.19
DCF	β	0.07	0.01	8.25	0.00	0.05	0.09
	Constant	39.04	1.23	31.82	0.00	36.63	41.45
RIVM	β	0.19	0.02	10.39	0.00	0.15	0.23
	Constant	34.01	1.31	25.93	0.00	31.44	36.59
MBVM	β	0.71	0.03	21.10	0.00	0.65	0.78
	Constant	14.42	1.57	9.17	0.00	11.33	17.51

	DDM	DCF	RIVM	MBVM
Obs.	708	708	708	708
Prob > F	0.00	0.00	0.00	0.00
R^2	0.05	0.12	0.25	0.54

[1] *Panel A depicts the low R&D subsample OLS regression results of univariate regressions Share Price =* $\alpha + \beta V^M + \varepsilon$*, where a is the constant,* V^M *is the value estimate using the model M = DDM, DCF, RIVM, or MBVM and* ε *is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. The ascendant order of explanatory power of the regressions is DDM, DCF, RIVM and MBVM.*

[2] *Panel B depicts the high R&D subsample OLS regression results of univariate regressions Share Price =* $\alpha + \beta V^M + \varepsilon$*, where a is the constant,* V^M *is the value estimate using the model M = DDM, DCF, RIVM, or MBVM and* ε *is the regression residual, using robust standard errors to address heteroscedasticity. T-values test the constant and coefficients on the equality to 0 and p-values show the significance. The ascendant order of explanatory power of the regressions is DDM, DCF, RIVM and MBVM. Comparing the two subsamples, DDM and RIVM have more explanatory power in the low R&D subsample, DCF has equal explanatory power in both subsamples and MBVM has more explanatory power in the high R&D subsample.*

3.2.6.5. Hypothesis 4 Assessment

H4: Valuations for companies with zero or low R&D expenditure are better in terms of bias, accuracy and explainability than the valuations for companies with high R&D expenditure, whilst the models' performance ranking remains equal to the main analysis ranking.

From the aforementioned results, the hypothesis is examined. Concerning the bias and accuracy, the FBVMs perform best in the low R&D subsample, while the MBVM using one year ahead consensus forecasted earnings has better performance in the high R&D subsample. In particular, the MBVM is superior to the FVBMs in the two subsamples, which contradicts the literature but is in accordance with the empirical evidence of the main analysis. Within the FBVMs, the RIVM is unsurpassable in both subsamples, however mixed evidence depending on the central tendency measure inspected arises for the third and fourth place of the ranking, similar to the hypothesis 2 of the main analysis. Nevertheless, since the subsamples stock prices and valuations are right-skewed, the mean is prejudiced by the outliers' effect, whilst the median maintains its estimation. Hence, considering the median, the DCF outperforms the DDM in terms of bias and accuracy.

Regarding explainability, the results are clearer. All the FBVMs have more explanatory power in the low R&D expenditure subsample, with the R^2 being supported with higher coefficients and lower constants for this subsample than for the high R&D subsample. Contrarily, the MBVM has higher explanatory power on the high R&D subsample. Nevertheless, the models' performance ranking is equal in both subsamples and equal to the main analysis. From the highest explainability to the lowest, the ranking is MBVM, RIVM, DCF and DDM.

Francis et al. (2000) analyses the FBVMs valuations for different R&D expenditures. Similar to the authors, I infer that for all of the performance measures – bias, accuracy and explainability – the RIVM is superior to the DDM and DCF. Contrarily to their findings, I detect divergences in the performance of both subsamples, with the low R&D expenditure subsample culminating in better bias, accuracy and explainability than the high R&D subsample. This evidence reflects the Schreiner and Spremann (2007) findings, as the researchers conclude that valuations for high R&D expenditure companies are penalised, and the Sougiannis and Yaekura (2001) findings, as they deduce that the valuation models have greater accuracy in companies with low R&D expenses. One possible explication for this is that the R&D investments understate accounting flows, as earnings and cash flows, hence valuations based on these flows will be lower.

Therefore, for bias, accuracy and explainability, it is possible to conclude that FBVMs are better off valuing companies with zero or low R&D expenditure than with high R&D investments, while the MBVM is better off valuing companies with high R&D expenditures. The models' performance ranking is analogous to the three performance measures in the two subsamples and is congruous with the main analysis: MBVM has the best performance, followed by the RIVM, DCF and DDM, respectively.

Although the performance ranking remains equal to the main analysis ranking and the FBVMs indeed perform better in the three performance measures when valuing companies with zero or low R&D expenditure, the MBVM performs better when valuing companies with high R&D expenditure.

Hypothesis 4 is rejected.

3.2.7. Sensitivity Analyses

The literature contemplates the influence of the models' assumptions as highly critical to the value estimates produced. Hence, multiple sensitivity analyses are conducted to evaluate how alternative assumptions impact the valuation models, and to consequently assess if the aforementioned findings are robust or vulnerable to the distinct assumptions.

The assumptions that are further scrutinized are the ones that the literature considers more controversial and capable of originating different valuations. However, before conducting the sensitivity analyses, it is necessary to highlight that the MBVM is excluded from the investigation because this model is not based on the same assumptions as the FBVMs. Due to its different technique to value equity, the MBVM has an independent sensitivity analysis concerning the selection of comparable companies and the computation technique of the benchmark multiple.

3.2.7.1. Flow-Based Valuation Models Sensitivity Analyses

All the results regarding the FBVMs analyses are displayed in table 17.

3.2.7.1.1. Market Risk Premium (MRP) Assumption

The MRP influences the FBVMs indirectly via the cost of equity (when using the capital asset pricing model). A sensitivity analysis using 2, 4 and 8% MRP is conducted.

The analyses suggest that a higher MRP is associated with lower valuation errors. Accuracy and bias are best at 8% MRP for the RIVM and DCF, while the DDM performs best at the previously assumed 6%. Regarding explainability, the higher the MRP, the bigger is the explanatory power of all models, thus the three FBVMs value estimations explain more of the stock price variability when the MRP increases. The coefficients of all models are the smallest for the 2% MRP and then increase greatly as the MRP grows to 8%.

Comparing the models, at lower MRP levels (2 and 4%), the DDM outperforms the RIVM and DCF in bias and accuracy. However, when the MRP rises, the RIVM is superior, as in the original assumption scenario (MRP equal 6%). Concerning explainability, for all the MRP assumptions, the RIVM is always the best performer, followed by the DCF and DDM, respectively.

A greater MRP results in a greater cost of equity and, when the discount factor is greater, the value estimates produced by the FBVMs are lower. Therefore, a higher MRP and, consequently, a higher cost of equity seems to yield more reasonable results as the performance of the valuation models in terms of bias, accuracy and explainability is better (except for the DDM that is less biased at 4% MRP). The models' performance ranking remains in the high

MRP assumption, whilst in the low MRP scenarios (2 and 4%), the DDM outperforms the other FBVMs in terms of bias and accuracy, suggesting that the models' ranking is vulnerable to low MRP assumptions but robust to high MRP assumptions.

3.2.7.1.2. Perpetual Growth Rate (g) Assumption

The flow-based models comprise a TV component in their computation to reduce the forecast horizon, which makes the models highly dependent on a long-term growth rate to portray the future flows of the company. A sensitivity analysis is executed with 0, 2 and 6% perpetual growth rate assumptions.

The analyses propound that a lower g results in lower valuation errors for the DCF and RIVM, while the DDM performs best at 2% perpetual growth. In concrete, the DCF and RIVM have superior accuracy and are less biased at 0% growth levels than at any other g assumption. Considering explainability, the lowest is the g, the greatest is the explanatory power of the models and their coefficients, implying that the correlation between the models' value estimates and the actual stock prices is highest when the assumed growth is 0%.

Juxtaposing the models, at all growth rate assumptions, the RIVM superiority prevails at all performance measures, as in the original assumption (g equal 4%) scenario. The only exception is when considering the mean APEs and SVEs at g = 6%, where the DDM outperforms the RIVM in bias and accuracy.

The worsening of the models' performance on an increase of the perpetual growth rate is most probably because some firms have low cost of equity, and when the growth rate becomes higher, the TV denominator – cost of equity minus perpetual growth rate – and consequently the TV component become negative, which remarkably minimizes the estimated equity value due to the high proportion that the TV comprehends in the valuations (Francis et al., 2000). Therefore, it seems more appropriate to apply a relatively low perpetual growth rate when conducting equity valuations. Nevertheless, the RIVM superiority remains in all the g assumptions, evidencing that the results are robust to this alteration.

3.2.7.1.3. Forecast Horizon Assumption

The forecast horizon directly influences the FBVMs as the degree of forecasted data incorporated in the valuation process varies according to the magnitude of the horizon. However, limitations on the number of observations arise when englobing longer forecast horizons due to fewer analysts' consensus forecasts being available for 3 years ahead EPS and DPS. Thus, to guarantee a sufficient number of observations, the forecast horizon sensitivity analysis only encompasses two levels: 2- and 3-year forecast horizon.

To ensure a high degree of parity between both analyses, the sample is reduced to 433 observations to have an equivalent number of observations for both forecast horizons. The original estimations for the 2-year forecast horizon are again computed for the new dataset.

For the DDM and RIVM, the valuation errors produced seem to not vary notably when the extra year of forecast horizon is included in the valuation process. Still, it is vital to point out that only when considering the median, the RIVM price scaled signed valuation errors for both horizons are statistically insignificant at 1% level, which advocates that the RIVM is unbiased. On the other hand, the DCF shows a slight improvement in bias and accuracy when including the 3rd year of the forecast horizon. Regarding explainability, the DDM and RIVM encompass the same explanatory power for both horizons, while the DCF moderately increases its explainability in the 3-year forecast horizon.

Contrasting the models' performance, in both forecast horizons the RIVM continues to outperform the other FBVMs in terms of bias, accuracy and explainability. Mixed evidence emerges again for the second place in the ranking in either horizon. Considering the mean, DDM performs better than the DCF in respect of bias and accuracy, while the DCF performs better than the DCF when analysing the median. For both forecast horizons, the original ranking of explanatory power remains, with the DCF being superior to the DDM.

These findings substantially reflect the literature. One of the main implementation issues of the DCF is that the short-term effect of CAPEX is not captured by this model because investments take time to materialize, and so the forecasting horizon must be sufficiently large to capture the longer-term impact of CAPEX (Penman, 2013). Hence, when the extra year is included, the DCF valuation errors decrease, which strengthens the model's bias and accuracy, and the explanatory power rises. Contrarily, the forecast horizon expansion does not significantly improve the performance of the DDM and RIVM. To conclude, although the DCF depicts improvements, the performance ranking remains, making the original analysis robust to forecast horizon alterations.

3.2.7.1.4. FBVMs Sensitivity Analyses Assessment

In general, the FBVMs best results are consummated under the original assumptions, except for the market risk premium that establishes better results for all models when the value is higher (MRP = 8%). In particular, the DCF and RIVM tend to perform better when the growth rate assumption is lower.

Overall, the RIVM is the model with the best performance for almost all of the assumptions. It is the most sensitive regarding explainability but still is the model with the highest explanatory power in all scenarios. The DDM is the least sensitive model to different assumptions as its valuation errors tend to be more constant than the other models' valuation errors. Contrarily, the DCF is the most sensitive model, presenting high fluctuations in its valuation errors when the assumptions are altered.

The models' performance ranking prevails in all the sensitivity analyses, which illustrates that the original analysis is robust to the mentioned alterations. The ranking is only vulnerable to low MRP assumptions (MRP equal to 2 and 4%), where the DDM outperforms the other FBVMs in bias and accuracy.

Table 17 - FBVMs Sensitivity Analyses for Market Risk Premium, Perpetual Growth Rate and Forecast Horizon

			APE		SVE		Regression Statistics		
Valuation Model	**Assumption**	**Obs.**	**Mean**	**Median**	**Mean**	**Median**	**R^2**	**Coeff.**	**Constant**
DDM	MRP = 2%	2,856	4.62 (0.00)	1.43 (0.00)	-2.31 (0.00)	-1.00 (0.00)	0.03 (0.00)	-0.02 (0.00)	46.57 (0.00)
	MRP = 4%	2,856	1.37 (0.00)	0.94 (0.00)	-0.12 (0.00)	-0.66 (0.00)	0.02 (0.00)	0.05 (0.00)	46.15 (0.00)
	MRP = 8%	2,856	0.79 (0.00)	0.87 (0.00)	-0.76 (0.00)	-0.86 (0.00)	0.09 (0.00)	0.68 (0.00)	40.60 (0.00)
DCF	MRP = 2%	2,856	25.61 (0.00)	7.18 (0.00)	-11.91 (0.00)	-5.58 (0.00)	0.02 (0.00)	-0.01 (0.00)	46.71 (0.00)
	MRP = 4%	2,856	8.63 (0.00)	2.19 (0.00)	5.29 (0.00)	1.86 (0.00)	0.03 (0.00)	0.01 (0.00)	45.34 (0.00)
	MRP = 8%	2,856	1.02 (0.00)	0.58 (0.00)	0.49 (0.00)	-0.09 (0.00)	0.13 (0.00)	0.19 (0.00)	36.58 (0.00)
RIVM	MRP = 2%	2,856	16.35 (0.00)	5.81 (0.00)	-8.33 (0.00)	-5.21 (0.00)	0.03 (0.00)	-0.01 (0.00)	46.40 (0.00)
	MRP = 4%	2,856	4.46 (0.00)	1.58 (0.00)	2.36 (0.00)	1.38 (0.00)	0.09 (0.00)	0.04 (0.00)	42.60 (0.00)
	MRP = 8%	2,856	0.42 (0.00)	0.37 (0.00)	-0.17 (0.00)	-0.28 (0.00)	0.42 (0.00)	0.66 (0.00)	23.18 (0.00)
DDM	g = 0%	2,856	0.82 (0.00)	0.88 (0.00)	-0.81 (0.00)	-0.88 (0.00)	0.10 (0.00)	1.00 (0.00)	39.39 (0.00)
	g = 2%	2,856	0.78 (0.00)	0.85 (0.00)	-0.75 (0.00)	-0.85 (0.00)	0.09 (0.00)	0.71 (0.00)	39.94 (0.00)
	g = 6%	2,856	1.25 (0.00)	0.90 (0.00)	-0.45 (0.00)	-0.74 (0.00)	0.01 (0.00)	0.05 (0.00)	46.83 (0.00)
DCF	g = 0%	2,856	0.81 (0.00)	0.54 (0.00)	0.20 (0.00)	-0.23 (0.00)	0.15 (0.00)	0.27 (0.00)	34.92 (0.00)
	g = 2%	2,856	1.06 (0.00)	0.58 (0.00)	0.57 (0.00)	-0.01 (0.00)	0.14 (0.00)	0.20 (0.00)	35.77 (0.00)
	g = 6%	2,856	6.28 (0.00)	1.53 (0.00)	3.08 (0.00)	1.12 (0.00)	0.03 (0.00)	0.01 (0.00)	45.87 (0.00)
RIVM	g = 0%	2,856	0.37 (0.00)	0.31 (0.00)	-0.02 (0.03)	-0.12 (0.00)	0.49 (0.00)	0.85 (0.00)	16.92 (0.00)
	g = 2%	2,856	0.40 (0.00)	0.31 (0.00)	-0.17 (0.00)	-0.23 (0.00)	0.47 (0.00)	0.64 (0.00)	20.00 (0.00)
	g = 6%	2,856	2.55 (0.00)	0.73 (0.00)	0.83 (0.00)	0.49 (0.00)	0.08 (0.00)	0.04 (0.00)	44.26 (0.00)
DDM	Forecast horizon = 2	433	0.73 (0.00)	0.77 (0.00)	-0.62 (0.00)	-0.75 (0.00)	0.03 (0.00)	0.27 (0.00)	45.79 (0.00)
	Forecast horizon = 3	433	0.72 (0.00)	0.77 (0.00)	-0.61 (0.00)	-0.75 (0.00)	0.03 (0.00)	0.23 (0.00)	46.09 (0.00)
DCF	Forecast horizon = 2	433	1.38 (0.00)	0.63 (0.00)	0.99 (0.00)	0.11 (0.00)	0.06 (0.00)	0.07 (0.00)	45.54 (0.00)
	Forecast horizon = 3	433	1.27 (0.00)	0.64 (0.00)	0.71 (0.00)	0.06 (0.00)	0.07 (0.00)	0.08 (0.00)	43.16 (0.00)
RIVM	Forecast horizon = 2	433	0.48 (0.00)	0.35 (0.00)	0.11 (0.00)	-0.03 (0.54)	0.30 (0.00)	0.38 (0.00)	30.07 (0.00)
	Forecast horizon = 3	433	0.49 (0.00)	0.36 (0.00)	0.15 (0.00)	0.01 (0.05)	0.30 (0.00)	0.37 (0.00)	29.93 (0.00)

Table 17 reports the FBVMs sensitivity to changes in the market risk premium, perpetual growth rate and forecast horizon. The table depicts the mean, median and statistical significance of APEs and SVEs for the FBVMs under the diverse assumptions. The significances are tested with t-tests for means and Wilcoxon sign-rank test for medians. P-

values are presented between parentheses. The last 3 columns show the key OLS regression results of the univariate regressions Share Price = $\alpha + \beta V^M + \varepsilon$, where a is the constant, V^M is the value estimate using the model M = DDM, DCF or RIVM, and ε is the regression residual, using robust standard errors to address heteroscedasticity. P-values on the equality to 0 are presented between parentheses. The best results are found under the original assumptions, except for MRP=8% and for low growth rate assumptions. RIVM is the best performer model for almost all assumptions. The DDM is the least sensitive model, while the DCF is the most sensitive. The models' performance ranking remains unaltered in all the analyses besides MRP=2 and 4%, where the DDM outperforms in bias and accuracy.

3.2.7.2. Multiple-Based Valuation Model Sensitivity Analyses

All the following analyses are based on the MBVM using one-year ahead consensus forecasted earnings as a value driver.

3.2.7.2.1. Selection of Comparable Companies Assumption

The selection of comparable companies has a great influence on the MBVM value estimation because the benchmark multiple is computed from the chosen peer companies. In fact, the selection of comparable companies is more an art than a science. Alford (1992) proclaims that selecting the comparable companies based on the first two digits of the SIC code is very effective. However, this is one of the key assumptions of the MBVM, hence different assumptions are scrutinized: the selection of comparable companies is conducted using one and three digits SIC code.

Constraints on the number of observations emerge when considering the three-digit SIC code, as only observations with at least ten peer companies are contemplated. Thus, to ensure a powerful level of comparability on the investigation, the dataset is lessened to 1,235 observations to guarantee an analogous number of observations for both analyses. Additionally, the initial estimations using the two-digit SIC code are computed once more for the new sample.

Table 18 panel A depicts the valuation errors and the regression statistics of the three assumptions. All the scenarios have very similar APEs and SVEs, with only a small increase in the mean APE and the median SVE for the one-digit SIC code. Concerning explainability, the R^2 are again hugely close, demonstrating only a little increase from the one-digit SIC code to the others. The coefficients and constants are also similar.

Due to the similarity of the results, paired tests are conducted and are displayed in Table 18 panel B. The SVEs are all statistically indifferent at a 5% level, meaning that the signed valuation errors produced by the three assumptions are equal. Thus, the valuation bias of the three scenarios is equal. However, the APEs of the one-digit SIC code compared to the ones of the other two assumptions are statistically different and bigger, which indicates that the one-digit SIC code assumption performs poorest in terms of accuracy. The APEs of the two and three digits SIC code are statistically indifferent, suggesting that the accuracy of both assumptions is equivalent.

To conclude, selecting comparable companies based on two or three digits SIC codes generate equivalent value estimates, valuation errors and models' explanatory power, while the one-digit SIC code assumption performs slightly worse in terms of accuracy and explainability. Therefore, it is correct to argue that the analysis is robust to the different processes of selecting comparable companies and that employing a narrower industry selection (three-digit SIC code) does not introduce any advantage comparing to the original two-digit SIC code assumption. Indeed, it solely introduces the disadvantage of reducing the sample observations.

Table 18 - MBVM Sensitivity Analyses to Different Methods of Selecting Comparable Companies

Panel A – Valuation Means, Valuation Errors of the Value Estimates and Key Regression Statistics [1]

			APE		SVE		Regression Statistics		
Assumption	**Obs.**	**Valuation Mean**	**Mean**	**Median**	**Mean**	**Median**	**R^2**	**Coeff.**	**Constant**
1 Digit SIC Code	1,235	41.60	0.40 (0.00)	0.28 (0.00)	0.03 (0.14)	-0.07 (0.00)	0.55 (0.00)	0.75 (0.00)	13.70 (0.00)
2 Digit SIC Code	1,235	42.67	0.38 (0.00)	0.28 (0.00)	0.03 (0.12)	-0.03 (0.01)	0.60 (0.00)	0.74 (0.00)	13.23 (0.00)
3 Digit SIC Code	1,235	42.66	0.38 (0.00)	0.28 (0.00)	0.03 (0.09)	-0.03 (0.01)	0.59 (0.00)	0.75 (0.00)	13.03 (0.00)

Panel B – Paired Tests of the Valuation Errors of the Value Estimates [2]

Error	**Absolute Prediction Errors**				**Signed Valuation Error**			
Assumption	**Mean**	**Mean Difference**	**Median**	**Median Difference**	**Mean**	**Mean Difference**	**Median**	**Median Difference**
1 Digit SIC Code	0.40	0.02 (0.00)	0.28	0.00 (0.00)	0.03	0.00 (0.99)	-0.07	-0.04 (0.07)
2 Digit SIC Code	0.38		0.28		0.03		-0.03	
2 Digit SIC Code	0.38	0.00 (0.56)	0.28	0.00 (0.46)	0.03	0.00 (0.32)	-0.03	0.00 (0.58)
3 Digit SIC Code	0.38		0.28		0.03		-0.03	
1 Digit SIC Code	0.40	0.02 (0.00)	0.28	0.00 (0.00)	0.03	0.00 (0.70)	-0.07	-0.04 (0.23)
3 Digit SIC Code	0.38		0.28		0.03		-0.03	

[1] *Panel A depicts the valuation mean, central tendency and statistical significance of the price scaled absolute prediction errors (APEs) and price scaled signed valuation errors (SVEs), and key regression statistics of MBVM under different methods of selecting comparable companies. The significance is tested with t-tests for means and Wilcoxon sign-rank tests for medians with respective p-values presented between parentheses. All valuation errors are statistically significant at a 5% level besides the mean SVEs under all assumptions. All assumptions have very similar bias, accuracy and explainability, with only a small increase in the performance from the 1-digit SIC code assumption to the other assumptions.*

[2] *Panel B depicts the comparison of the valuation errors of one SIC code assumption with the valuation errors of other SIC code assumption by applying paired t-tests for means and two-sample Wilcoxon rank-sum tests for medians. P-values are depicted between parentheses. All differences of SVEs and all differences between 2 and 3-digit SIC code assumptions are statistically insignificant at 5% level. Hence, selecting comparable companies based on 2 or 3-digit SIC code produces equal bias, accuracy and explainability, while the 1-digit SIC code performs worse in accuracy and explainability.*

3.2.7.2.2. Benchmark Multiple Computation Assumptions

The computation of the benchmark multiple represents the process of averaging the comparable companies' multiples. In fact, various averaging techniques have the potential to generate different results (Agrrawal, Borgman et al., 2010). Hence, a sensitivity analysis is conducted with the contrasting averaging techniques to compute the benchmark multiple. Median, weighted average mean and arithmetic mean are analysed and compared to the original harmonic mean. All averaging techniques are calculated following section 2.4.2.3.

Table 19 Panel A reports the valuation errors and regression statistics of the original assumption and the three new assumptions. The harmonic mean, median and weighted average mean computation techniques have equivalent APEs and SVEs, which suggests these approaches have equivalent accuracy and bias. However, the APEs and SVEs of the arithmetic mean are higher, implying that this approach is less accurate and more biased. Regarding explainability, all the R^2 are very close, with the harmonic mean and median having 1 and 3% more explanatory power than the weighted average mean and arithmetic mean, respectively.

Since the results present high similitude, paired tests are performed in Table 19 panel B. All the results are statistically different at a 5% significance level besides the median APEs of the harmonic mean and median averaging techniques, suggesting these two techniques have the same accuracy. The harmonic mean and median have the best accuracy, followed by the weighted average mean and the arithmetic mean. Concerning bias, in mean measures, the harmonic mean performs best, followed by weighted average mean, median and arithmetic mean. However, in median measures, the median averaging technique is less biased than the harmonic mean but solely for a small difference.

These findings coincide with the literature. To compute the benchmark multiple, harmonic mean, median and weighted average mean averaging techniques are best and produce equivalent bias, accuracy and explainability, while the worst performance is generated by the arithmetic mean. As expected, the arithmetic mean performs poorest due to the approach being sensitive to outliers, which results in upward biased valuations. Hence, due to the similarity of the results when excluding the weaker arithmetic mean, the original analysis is robust to alterations of the benchmark multiple averaging techniques.

Table 19 - MBVM Sensitivity Analyses to Different Methods of Computing the Benchmark Multiple

Panel A – Valuation Means, Valuation Errors of the Value Estimates and Key Regression Statistics [1]

			APE		SVE		Regression Statistics		
Assumption	**Obs.**	**Valuation Mean**	**Mean**	**Median**	**Mean**	**Median**	**R²**	**Coeff.**	**Constant**
Harmonic Mean	2,856	45.32	0.34 (0.00)	0.25 (0.00)	0.01 (0.21)	-0.02 (0.00)	0.54 (0.00)	0.76 (0.00)	13.62 (0.00)
Median	2,856	46.72	0.34 (0.00)	0.25 (0.00)	0.05 (0.00)	0.00 (0.36)	0.54 (0.00)	0.73 (0.00)	13.87 (0.00)
Weighted Average Mean	2,856	46.14	0.35 (0.00)	0.25 (0.00)	0.04 (0.00)	-0.02 (0.46)	0.53 (0.00)	0.73 (0.00)	14.29 (0.00)
Arithmetic Mean	2,856	56.88	0.48 (0.00)	0.35 (0.00)	0.29 (0.00)	0.21 (0.00)	0.51 (0.00)	0.59 (0.00)	14.16 (0.00)

Panel B – Paired Tests of the Valuation Errors of the Value Estimates [2]

Error	Absolute Prediction Errors				Signed Valuation Error			
Assumption	**Mean**	**Mean Difference**	**Median**	**Median Difference**	**Mean**	**Mean Difference**	**Median**	**Median Difference**
Harmonic Mean	0.34	0.00 (0.00)	0.25	0.00 (0.31)	0.01	-0.04 (0.00)	-0.02	-0.02 (0.00)
Median	0.34		0.25		0.05		0.00	
Harmonic Mean	0.34	-0.01 (0.00)	0.25	0.00 (0.01)	0.01	-0.04 (0.00)	-0.02	0.00 (0.00)
Weighted Average Mean	0.35		0.25		0.04		-0.02	
Harmonic Mean	0.34	-0.14 (0.00)	0.25	-0.10 (0.00)	0.01	-0.28 (0.00)	-0.02	-0.23 (0.00)
Arith. Mean	0.48		0.35		0.29		0.21	
Arith. Mean	0.48	0.14 (0.00)	0.35	0.10 (0.00)	0.29	0.24 (0.04)	0.21	0.21 (0.00)
Median	0.34		0.25		0.05		0.00	
Median	0.34	-0.01 (0.00)	0.25	0.00 (0.01)	0.05	0.01 (0.00)	0.00	0.02 (0.00)
Weighted Average Mean	0.35		0.25		0.04		-0.02	
Weighted Average Mean	0.35	-0.13 (0.00)	0.25	-0.10 (0.00)	0.04	-0.25 (0.00)	-0.02	-0.23 (0.00)
Arith. Mean	0.48		0.35		0.29		0.21	

[1] *Panel A depicts the valuation mean, central tendency and statistical significance of price scaled absolute prediction errors (APEs) and price scaled signed valuation errors (SVEs), and key regression statistics of the MBVM under different methods of computing the benchmark multiple. The significance is tested with t-tests for means and Wilcoxon sign-rank tests for medians, with respective p-values presented between parentheses. All valuation errors are statistically significant at 5% level besides the mean SVE for the harmonic mean and the median SVEs for the median and weighted-average mean assumptions. Overall, harmonic mean, median and weighted average mean averaging methods have very similar bias, accuracy and explainability, while the arithmetic mean performs worst in the three performance measures.*

[2] *Panel B depicts the comparison of the valuation errors of one averaging method with the valuation errors of another averaging method by applying paired t-tests for means and two-sample Wilcoxon rank-sum tests for medians. P-values are depicted between parentheses. All differences are statistically significant at 5% level besides the median APEs difference between the harmonic mean and median. The harmonic mean and median perform best in accuracy, followed by the weighted-average mean and the arithmetic mean, respectively. Concerning bias, when analysing the mean, the harmonic mean performs best, followed by weighted average mean, median and arithmetic mean, respectively. However, when analysing the median, the median performs best, the harmonic mean and weighted average mean perform similar and the arithmetic mean performs the worst.*

3.2.7.2.3. MBVM Sensitivity Analysis Assessment

Overall, the MBVM using one-year ahead consensus forecasted earnings best performance is achieved under the original assumptions. The model demonstrated to be resilient to the different assumptions, therefore the main analysis is robust to alterations on the critical assumptions.

Moreover, it must be emphasized that selecting comparable companies based on the 3-digit SIC code does not carry any advantage for the performance of the MBVM. In fact, this procedure of narrowing more the industry to ensure a greater match between the peer companies' characteristics works as well as the less narrowed 2-digit SIC code assumption.

3.3. Interim Conclusion and Limitations

The empirical evidence of this large sample analysis suggests that among the valuation models examined, the MBVM using one-year ahead consensus forecasted earnings as a value driver performs best in terms of bias, accuracy and explainability. This result refutes the literature, which argues that FBVMs are superior to MBVMs. Still, in accordance with the literature, this analysis advocates the RIVM superiority within the FBVMs group in the three performance measures. Overall, the large sample analysis depicts the following descendent ranking of performance: MBVM, RIVM, DCF and DDM, even though the latter two sometimes alternate their order of superiority. This models' performance ranking is robust to alterations in the critical assumptions, except for the low MRP assumptions (MRP = 2 and 4%), where the least sensitive DDM outperforms the other FBVMs.

Concerning the impact of the R&D expenditure on the performance of the valuation models, comparing to the main analysis, the three FBVMs perform best when valuing companies with zero or low R&D expenditure, while the MBVM performs best when valuing companies with high R&D expenditure. Nevertheless, the models' performance ranking stated in the previous paragraph prevails regardless of the R&D expenditure.

Having said that, it is essential to indicate that the large sample analysis findings are limited to the sample selection criteria and therefore may not be representative of all companies. In fact, the analysis is restricted to U.S. companies that are not start-ups (i.e., young growth companies), because selecting criteria as positive earnings and positive cash flows tend to eliminate companies that are in an early stage of the life cycle. Additionally, financial and utility companies are eliminated from the sample, hence the aforementioned findings are also not representative of these two industries.

Moreover, the analysis takes for granted several assumptions necessary to implement the different valuation models. Although the sensitivity analysis proved that the findings are robust to assumptions alterations, these assumptions may not be representative of the reality as most of them depend on the actual economic conditions at the time of the valuation.

To terminate, the 2008 financial crisis (that is included on the investigated horizon) can prompt distortions on the market share prices and, consequently, on the estimated valuation errors, which may also affect the analysis findings.

4. SMALL SAMPLE ANALYSIS

The large sample analysis provides satisfactory insights about the valuation models and their statistical relations across a wide variety of companies, however it is insufficient to capture the real valuation procedure applied by market participants. Since the practical procedures aren't perceptible in the large sample analysis and may vary from the previous analyses' inferences, a one company small sample analysis is conducted to inspect in detail the valuation process employed by market participants, namely financial analysts. The data utilized in this section is mainly from equity analyst reports and financial statements.

Although the theory propounds that disparate valuation models result in the same valuations, the large sample analysis could disclose an outperformance of the MBVM over the FVBMs and a superiority of the RIVM within the flow-based models. Given the practical utility of the models, this section analyses two sell-side equity analyst reports to investigate which models are indeed used by financial analysts and how they are implemented.

The small sample analysis starts with a review of the literature concerning the usage of the models by equity analysts. Based on the evidence, a corresponding hypothesis is developed. Afterward, a company is selected and briefly examined, with the emphasis being on the business model, strategy and financials. Then, two sell-side equity analyst reports from the commencement of 2014 are discussed before a conclusion concerning the small sample analysis and the hypothesis being presented.

The scrutinized reports are from 2014 because the chosen company only has observations in the large sample for the fiscal period of 2006 to 2013, in which the stock price four months after the fiscal year-end corresponds to January 2014.

4.1. Valuation Models and Sell-Side Equity Analysts

For estimating a target price, sell-side equity analysts use several valuation models as the FBVMs and MBVMs. Succeeding to the literature focus on the conceptual relative performance of the models (e.g., Francis et al., 2000 and Liu et al., 2002), the attentiveness about which models are usually employed and how they are implemented by analysts has increased (Demirakos et al., 2004; Imam, Barker et al., 2008).

Demirakos et al. (2004) claim that the model selection is influenced by the company's industry membership due to its particularities, although the clients' validity and the analyst familiarity with the model are also critical. Nevertheless, they state that analysts implement mostly the MBVM, specifically the price-to-earnings models, whose appliance intensifies even more in stable industries. Among FBVMs, the RIVM is hardly ever employed and the DCF is the favourite model (Hand, Coyne et al., 2017). Imam, Barker et al. (2008) attribute the favouritism of the DCF in the past years to an increase in the clients' interest in the model. However, the researchers argue that the practical implementation issues of the DCF result in the MBVM being the main valuation model, with the former solely serving as a supplement to communicate the information to the clientele. Indeed, Demirakos et al. (2010) recognize the superiority of the MBVM using the price-to-earnings as a value driver over the DCF.

Regarding the MBVM selection of peer companies, De Franco, Hope et al. (2015) ascertain that analysts tend to select the comparable companies with bigger valuations to estimate an overly optimistic target price, even though other features as the expected equivalent growth opportunities may be the motivation for such selection.

4.2. Hypothesis 5 Development

This small sample analysis intends to determine which valuation models sell-side equity analysts employ in reality. The literature asserts that analysts use the MBVMs to value companies due its straightforwardness in conjunction with the bigger implementation issues of the FBVMs (Demirakos et al., 2004; Imam, Barker et al., 2008; Demirakos et al., 2010). Although this may vary depending on the industry and situation, the MBVMs are widely used in stable industries (Demirakos et al., 2010). Additionally, the literature depicts that analysts also tend to apply the DCF model because of its increasing popularity amongst clients, while the RIVM and DDM are infrequently employed (Demirakos et al., 2004; Imam, Baker et al., 2008). Hence, due to the industry stability of the selected company (presented in the next section), the non-complexity of the MBVMs and the increasing interest among the DCF, the following hypothesis is established:

H5: Multiple-Based Valuation Models are the main valuation model employed by sell-side analysts, followed by the Discounted Cash Flow Model due to its popularity.

The first part of the hypothesis is in accordance with the large sample analysis findings that MBVMs perform better than FBVMs in terms of bias, accuracy and explainability. However, the expected utilization of the DCF and the underutilization of the RIVM contradict the previous analyses, as the findings suggest that the RIVM outperforms within the FBVMs group.

4.3. Company Selection Criteria

The selected company for the small sample analysis has to fulfill various requirements. Firstly, it has to be present in the 2,856 observations of the large sample analysis final dataset, which consists only of U.S. public firms with available Security and Exchange Commission (SEC) filings.

Although Francis et al. (2000) state that the industry membership does not jeopardize the valuation models' performance, Demirakos et al. (2004) argue that the industry stability has the potential to influence which valuation models are employed by analysts. In concrete, they claim that analysts are more probable to employ MBVMs when valuing companies from stable industries. Due to the outperformance of the MBVM in the large sample analysis, the selected company must belong to a stable industry.

As previously discussed, the literature regarding which valuation model equity sell-side analysts apply in practice identifies the MBVM as the primary model (Demirakos et al., 2004). However, when the valued company is further diversified in its operations, the MBVM tends to underperform due to the difficulty of selecting comparable companies that correspond to the risks and operations of the company being valued. Hence, to undeniably test the MBVM preference among analysts, the selected company should be considerably diversified. This criterion also tests how the analysts (that reflect the models' practicality) address the implementation issues.

Furthermore, since valuation models are anchored on the fundamentals of the company, they are expected to have superior performance for a mature and large company. Thus, the chosen company must be well established and sufficiently mature.

Considering all the above criteria, the selected company for the small sample analysis is The Walt Disney Company (NYSE: DIS).

4.4. Company Analysis

4.4.1. The Walt Disney Company (NYSE: DIS) Overview

From now on solely Disney, founded in 1923, it is a mature and well-diversified company in the entertainment industry with operations in five business segments. In a brief summary, the studio entertainment segment produces and purchases rights for motion pictures, movies, music recordings, live stage performances and live entertainment experiences. The media network segment comprises television and radio stations, broadcast and cable television networks. The parks and resorts segment encompasses the operation of theme parks, resorts and hotels, Disney Vacation Club and Disney Cruise Line. The direct-to-consumer products segment includes the commercialization of a vast variety of products based on Disney's intellectual property, as well as video streaming subscription services. Finally, the interactive segment produces and distributes branded multi-platform games and branded online services. In concrete, the media network segment has the biggest revenue, accounting for approximately 45% of the total revenues, followed by the parks and resort segment (31% of total revenues). The smallest revenue segment source is the interactive, accounting for only 2% of Disney's revenues in 2013 (The Walt Disney Company, 2013).

Even though Disney itself is a tremendously recognized brand, it owns and operates other various well-known brands, as Marvel, Pixar, Twentieth Century Studios, ESPN, Fox and National Geographic, among several others (The Walt Disney Company, 2013). To better understand the company, a SWOT analysis is conducted in table 20.

Table 20 - Swot Analysis for The Walt Disney Company

Strengths	Weaknesses	Opportunities	Threats
1. Strong Brand Awareness	**1. Vulnerable to North American economy** (U.S. represents approximately 75% of bulk revenue)	**1. Expansion into New Markets** (as China and India)	**1. Lack of Innovation and Competitors New Technology**
2. Established Market Position	**2. Sky-High employees training costs**	**2. Increasing Demand for Videogames and Streaming Platforms**	**2. Core Competency Problem resulting in Improper Resources Usage**
3. Worldwide Presence	**3. Lack of New Products**	**3. Current Low Level of Marketing can be Enlarged**	**3. Parks and Resorts Segment Vulnerability to Sanitary Problems** (e.g., global pandemics)
4. Selling Opportunities between Segments (e.g., a new movie made by studio entertainment leads to selling toys and creating attractions in the amusement parks)	**4. Criticisms that Prejudice the Brand** (e.g., stereotypical characterization of only white characters)	**4. Technological Innovation**	**4. Upward Trend in Piracy Content**
Source: The Walt Disney Company (2013)			**5. Industry Consolidation**

Table 20 depicts the SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis for The Walt Disney Company. Overall, Disney's potential materializes from its established market position, diversification and strong brand awareness. However, Disney must innovate and improve its competency problems to remain competitive.

4.4.2. The Walt Disney Company (NYSE: DIS) Financials

This section provides some financial insights about Disney for the period 2006-2013, which is the time horizon that Disney observations are available in the final dataset of the large sample analysis.

Figure 2 contains financial information about the company. In 2013, the majority of the assets are non-current (80%) and hence, are fixed for the long term. At 57%, Disney finances more than half of its assets with shareholders' equity ($48.15B), with only 14% of its total assets being financed by current liabilities ($13.29B). With a current ratio – current assets divided by current liabilities – of 1.21, Disney depicts a sufficiently strong financial condition to ensure its short-term sustainability (The Walt Disney Company, 2013).

Regarding the income statement development from 2006 to 2013, the revenues, gross profit, EBIT and net income are steadily growing over the years, excluding the year 2009 where the 2008 financial crisis impact is reflected. It is important to notice that the gross profit increased significantly in 2012. The CEO, Robert Iger, attributes this achievement to the long-term strategy and the remarkable investments that Disney has made, which led to improved results in each of the business segments (The Walt Disney Company, 2012).

The operating cash flows are positive and demonstrate a stable increase over the years, indicating that Disney generates yearly cash inflows to support and improve its operations. This is accompanied by an overall negative increase in the investing and financing cash flows. A negative growing investing cash flow suggests that the company has been investing cash into the future, while a negative growing financing cash flow implies that Disney has been repurchasing stocks, paying dividends and/or retiring debt. All these cash flows developments express the matureness and stability of Disney, which can also be observable by the gradual increase in the free cash flows.

Hence, considering solely these peripheral analyses, I conclude that from 2006 to 2013 Disney accomplished a satisfactory development.

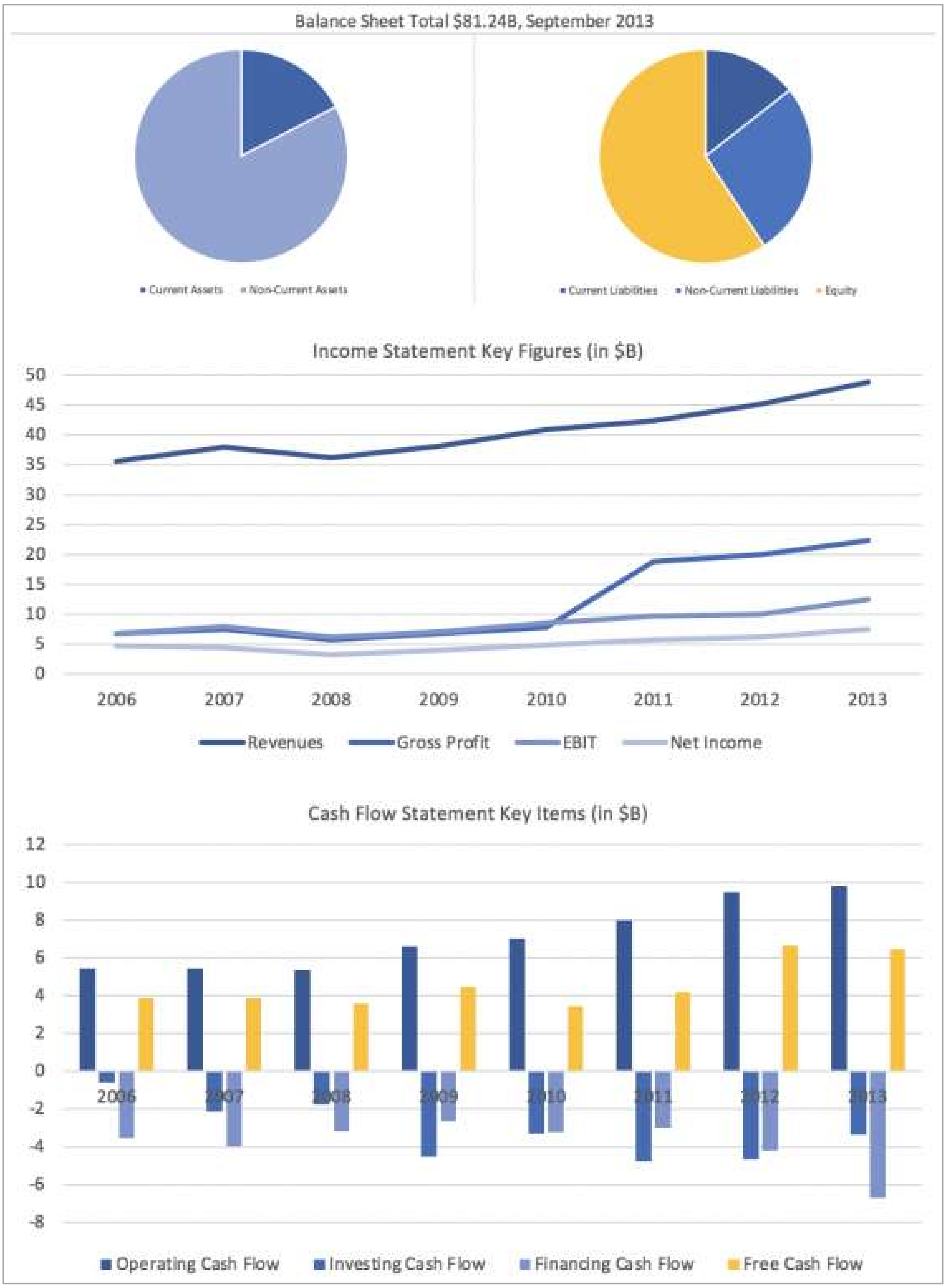

Figure 2 - Financial Information about The Walt Disney Company

(all figures in $ billions)

4.4.3. The Walt Disney Company (NYSE: DIS) Results from the Large Sample Analysis

To ensure a comparison point for the next section concerning the models' preferences of sell-side equity analysts, the figure 3 provides the large sample analysis value estimates of the four models and the corresponding share price four months after the fiscal year-end (PRC4). Since Disney's fiscal year ends in September, the value estimates and stock prices presented are the monthly prices of January.

Disney valuation estimates corroborate the large sample analysis conclusion. The MBVM outperforms the FBVMs in seven of the eight years analysed, while the RIVM is superior in 2010. The popular DCF tends to significantly overestimate value, while the DDM constantly underestimates it. In absolute terms, in the years examined, the DDM value estimates deviate more from the stock price than the ones from the DCF.

Hence, the models' preferences of the analysts to value Disney should be firstly the MBVM, followed by the RIVM, DCF and DDM, respectively.

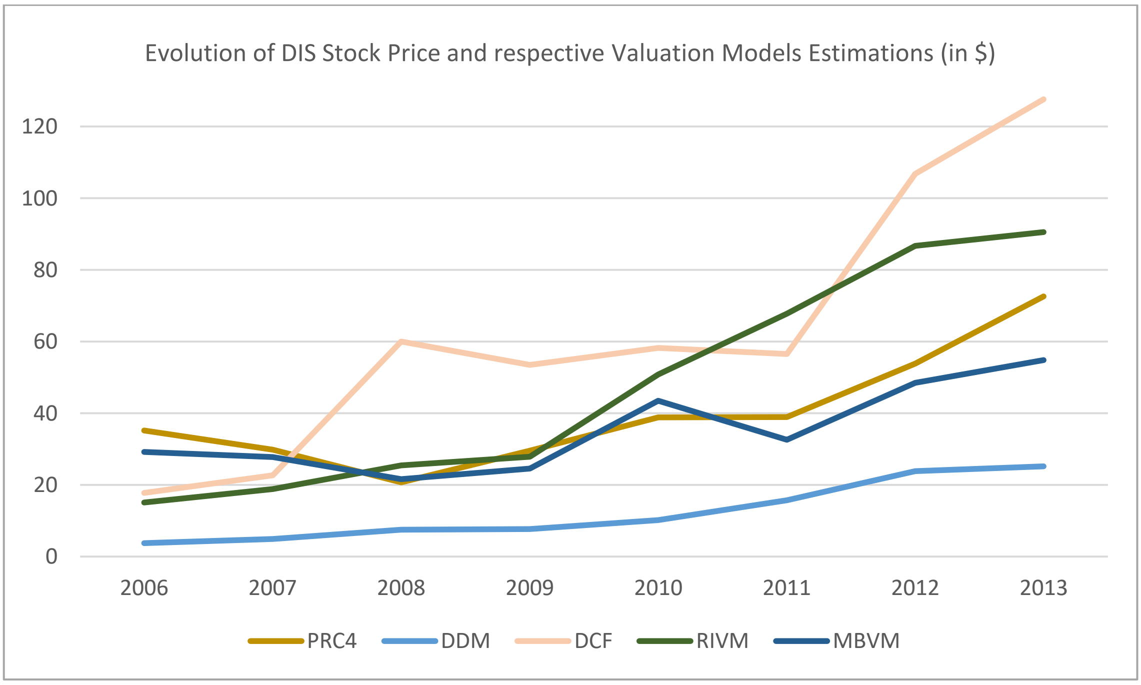

Figure 3 - Evolution of The Walt Disney Company Stock Price and respective Valuation Models Estimates

4.5. Sell-Side Equity Analyst Reports Examination

Equity analysts collect data about the company to forecast the accounting flows and subsequently to estimate the firm value (Demirakos et al., 2010). The valuation is conducted to provide a recommendation about the expected future performance of the company and its stock price (Asquith, Mikhail et al., 2005). Hence, an equity analyst report generally comprises forecasts, a value estimation (i.e., target price), a recommendation and the rationale for the recommendation (Asquith, Mikhail et al., 2005; Demirakos et al., 2010; De Franco, Hope et al., 2015). Even though some proclaim that such reports do not encompass new information, Asquith, Mikhail et al. (2005) detect that analyst reports include newborn information that prompts the stock prices to react to the new enlightenments. Furthermore, the researchers discover that the "stronger" is the recommendation justification, the bigger is the market's reaction.

The following sections present the examination of two sell-side equity analyst reports for Disney with dates the closest to the end of January 2014.

4.5.1. Morgan Stanley Sell-Side Equity Analyst Report

The investment bank Morgan Stanley published a sell-side equity analyst report for The Walt Disney Company (NYSE: DIS) on the 24th February of 2014 (Swinburne et al., 2014). Although the involved analysts prospect a positive future growth for Disney, they maintain their "equal-weight" recommendation from the last report (equal-weight means hold in Morgan Stanley's terminology).

The expected Disney's future growth is formulated on the analysts' optimism regarding the movie *Frozen*. Until the report date, the movie reported $950 million in revenue, with the analysts expecting an equal momentum for the following months. Moreover, they state that the movie has an exceptionally high return on investment (ROI), which will drive Disney's profitability not only on the studio entertainment segment but also on the other business segments (e.g., the movie helps the consumer products sales). Hence, as the analysts expect the incremental profits to rise, Disney's predominant performance over its peers is anticipated to continue, thereby helping the company to meet the analysts' expectations. Additionally, the analysts also contemplate that the new Marvel franchises *Avengers 2* and *Star Wars Episode 7* will contribute to the future growth of Disney.

Nevertheless, the equal-weight recommendation remains due to specific risks. The analysts argue that Disney has more cyclicality than its competitors, which exposes the direct-to-consumer products and the parks and resorts segment to additional threats. Furthermore, they expect Lucasfilm and ESPN to comprise limited growth, as the respective industries are stabilizing.

Based on the above viewpoints about the future, the analysts articulate their forward-looking opinions by forecasting the critical value drivers that are later incorporated in the pro-forma financial statements. Thus, a 4-year (2014 to 2017) pro-forma balance sheet, income statement and cash flow statement are developed to serve as the basis for the valuation process. The valuation model adopted is uniquely the multiple-based valuation model, although they employ three multiples, the 3-year ahead forward adjusted P/E, forward adjusted P/FCF and forward EV/EBITDA. Hence, with a 3-year forecast horizon, the value estimate comprises the equity and entity perspectives. The valuation estimates a target price of $80.00, which is fairly proximate to the actual share price of $80.13 on the 21st February of 2014.

The report encompasses two cases for the specified multiples, one using the actual price and another using the target price. The advocated multiples are depicted in table 21.

Table 21 - Morgan Stanley Multiples for The Walt Disney Company

Multiple	2014 Multiple using…	
	Actual Price	**Price Target**
Forward Adjusted Price/Earnings	15.5x	16.0x
Forward Adjusted Price/FCF	17.8x	18.4x
Forward EV/EBITDA	9.6x	9.9x

Table 21 reports the multiples of Disney as they are disclosed in the report issued by Morgan Stanley in February 2014.

The analysts' MBVM preference over the FBVMs is clear, which is in line with the large sample analysis findings and with Fernandez (2001) and Demirakos et al. (2004), who argue that most of the analysts favour the MBVM. Additionally, this evidence partly supports hypothesis 5.

Concerning the implementation of the valuation procedure, the equity report does not specify any calculation nor explanation on how the multiples have been computed. In concrete, the report does not contain which firms have been used as comparable firms, neither explains which averaging method has been utilized.

As previously scrutinized, the MBVM does not require the same critical assumptions of the FBVMs, however the model has other implementation issues that analysts must tackle. The literature recommends the avoidance of MBVMs for diversified companies due to the difficulty of selecting matching peer companies for a company operating in various industries (De Franco, Hope et al., 2015). To address this problem, instead of looking to the company as a whole, the analysts divide Disney according to its business segments. Then, for each segment, they present a detailed forecast and compute a benchmark multiple. Afterward, to conduct the valuation, Disney's final multiple is assumed equal to the average of the segments' multiples. This approach circumvents the peers' selection issue by considering each business segment as a "company", which permits the analysts to make a superior selection of the benchmark companies.

Another implementation issue refers to the growth rate utilized to forecast the main value drivers. Again, the analysts break down Disney according to its business segments in an attempt to collect as many insights as possible about every operation. Subsequently, they consider macro-economic and industry circumstances before estimating a final growth rate for each business segment. The used growth rates vary from 6 to 9% depending on the business segment, which is higher than the large sample analysis growth rate of 4%. Nevertheless, they perform a sensitivity analysis with two scenarios for the growth rates, an optimistic and a pessimistic scenario with higher and lower growth rates than the base case, respectively. The contrasting growth rates generate dissimilar target prices, which corresponds to the large sample analysis evidence.

4.5.2. RBC Capital Markets Sell-Side Equity Analyst Report

The second sell-side equity analyst report for The Walt Disney Company (NYSE: DIS) examined is published by the investment bank RBC Capital Markets on the 26th February of 2014 (Bank et al., 2014). The analysts maintain their preceding recommendation of "outperform" (buy in the bank's terminology), meaning that they expected Disney to outperform the sector average throughout the next year.

This prospect is based on four main drivers. Firstly, the analysts appraise that the non-existence of short-term M&A targets will result in Disney continuing to return back capital to the stockholders, which is anticipated to cause a positive market reaction that will lead to an increase in the stock price. Secondly, they prospect that the increase in the parks' ticket prices by 15-21% and the opening of Shanghai's resort will raise the margins and revenues for the parks and resort segment. Thirdly, they foresee that the launch of the movies *Avengers 2* and *Star Wars Episode 7*, together with the partnership with Netflix (NASDAQ: NFLX) to produce four Marvel series will enhance the revenues of all business segments. Lastly, the strong results from the 2014 first quarter allowed Disney to beat EBIT analysts' expectations by approximately 10%, which created a good sentiment in the market. Furthermore, due to the movie *Frozen* prosperity, the analysts expect the recent past strong results to prolong into the near future.

However, the analysts also emphasize risks and uncertainties concerning Disney's future. In specific, the unsatisfactory performance of the interactive segment, that is Disney's weakest segment, intensifies the company risk as it creates concernments to the investors. Moreover, the media networks segment generates uncertainty for the upcoming due to the ratings worsen at the same time that the costs for sports rights are increasing and the competition is growing, which can result in the loss of some sports programmes that will severely jeopardize revenues. Generally, the increase of piracy content and the lessen of marketing expenditures also constitute additional risks for the long-term profitability of Disney.

Evolved from the aforementioned outlook, the analysts predict a value estimate for Disney. The main valuation model employed is the MBVM using three multiples, the 1-year ahead forward P/E, forward P/FCF and forward EV/EBITDA, presented on table 22. Hence, the equity and entity perspectives are depicted, and the multiples utilized are equivalent to the Morgan Stanley report but with a different time horizon. Additionally, as a complementary method, the analysts refer to the DCF, but no calculations nor value estimates derived from this model are illustrated in the report. Therefore, the valuation based on the MBVM estimates a target price of $89.00, which represents an 11.14% return considering the at the time current share price of $80.08.

Table 22 - RBC Capital Markets Multiples for The Walt Disney Company

Multiple	**2014 Multiple**
Forward Price/Earnings	19.3x
Forward Price/FCF	21.0x
Forward EV/EBITDA	11.7x

Table 22 reports the multiples of Disney as they are disclosed in the report issued by RBC Capital Markets in February 2014.

Similar to the Morgan Stanley report, the large sample analysis and the literature, the preference of the MBVM over the FBVMs is observable.

Concerning the valuation procedure, this equity report provides clarifications regarding the benchmark multiple computation. The analysts identify the companies that have been selected as peers – NASDAQ: VIAC, DISCA, FOX, SNI, TXW and VIAC. The six selected comparable companies are from the same major industry sector, represented by the first two-digit SIC code "48" (communications). Thus, the selection of comparable companies employed is in conformity with Alford (1992) and, consequently, with the large sample analysis. Nonetheless, the averaging method implemented is the arithmetic mean, which contradicts the large sample analysis and partly refutes the suggestions of the literature that the harmonic mean and median produce less biased results (Liu et al., 2002; Schreiner and Spremann, 2007).

Considering the growth rate implementation issue, the analysts develop the growth assumptions based on their viewpoints about the future performance. Specifically, they formulate for each business segment a comprehensive forecast, mainly for income statement items (no pro-forma statements), which generates growth rates between 4-6% contingent to the segment. These assumptions differ from the ones made by the Morgan Stanley analysts but are closer to the large sample analysis flat assumption of 4%. Still, a growth rate sensitivity analysis has been performed to assess the impact of variations in the business conditions that result in disparate levels of risk. By generating two extra scenarios, one concerning the downside potential with lower growth and the other the upside potential with higher growth (compared to the base case), the analysts create a price range from $75.00 in the downside scenario to $103.00 in the upside scenario.

4.6. Small Sample Analysis Summary and Hypothesis 5 Assessment

Either of the analysed reports apply the MBVM using the multiples forward price-to-earnings, forward price-to-FCF and enterprise value/EBITDA. Due to the emphasis that the analysts provide, the forward price-to-earnings seems preferable to the others. Both findings are in accordance with the literature that states the MBVM using the multiple forward P/E is superior to every other procedure (Kim and Ritter, 1999; Liu et al., 2002; Lie and Lie, 2002; Liu et al., 2007). However, there is no explanation on the reports about the MBVM preference over the FBVMs. I conjecture that one reasonable interpretation concerning the analysts' preference for the MBVM is that they attempt to make as few assumptions as feasible, in order to assemble a valuation process less dependent on the analysts' opinion.

For the small sample analysis, it is critical to appraise the valuation procedure. In fact, the valuation horizon utilized is two and three years, conditional on the report. Analysts try to make a sophisticated guess about the future, thus they prefer to do forecasts until three years long because they have more reliable insights for this period, while longer forecast horizons tend to be more uncertain. Therefore, the valuation horizon used by the examined analysts is consistent with Palepu et al. (2013) and the large sample analysis.

Concerning the forecasts, each report comprises a comprehensive earnings and free cash flow forecast for each business segment. Although cash flows seem to be a key driver of firm value (otherwise analysts wouldn't dedicate time to forecast them), none of the reports applies the DCF model. Hence, it is viable to conclude that analysts trust profoundly in their own forecasts of earnings as the main support for the valuation and that they address the company's diversification issue by forecasting each business segment separately. Additionally, both reports have a sensitivity analysis where the growth rate is altered, which illustrates the vulnerability of the valuation process to the analysts' assumptions, even for the MBVM.

The preference of the MBVM complies with hypothesis 5. However, none of the reports depict a valuation using the DCF, with only the RBC Capital

Markets report providing a small reference to it. Still, citations to the DDM and RIVM do not exist in any of the reports, which may indicate that the DCF reference is client driven, as discussed by Imam, Barker et al. (2008). Hence, hypothesis 5 cannot be rejected.

To conclude, by no means should the presented findings be generalized. These findings are solely specific to The Walt Disney Company (NYSE: DIS). For different companies and industries, analysts may alter their preferences and apply different models.

5. CONCLUSION

Due to the importance of firm valuation in real-world situations, this dissertation investigated the performance of distinct equity valuation models and some empirical options and assumptions. Although in theory, different models should yield equivalent value estimates, in practice they are vulnerable to implementation issues that can generate discrepancies in the derived value estimates. Therefore, this dissertation examined which models produced the most reliable equity value estimates, where the models assessed were the multiple-based valuation model (MBVM) using one-year ahead consensus forecasted earnings as a value driver and, within the flow-based valuation models (FBVMs) group, the dividend discount model (DDM), the discounted cash flow model (DCF) and the residual income valuation model (RIVM).

Prior studies presented evidence that RIVM was the most reliable model within the FBVMs group and that the MBVM using one-year ahead consensus forecasted earnings as a value driver had a superior performance than the other MBVMs, however empirical evidence comparing the FBVMs and the MBVM was rather limited. The literature review disclosed that most of the papers about the valuation models' reliability were outdated (as they studied observation periods long ago), while very few papers focused on a joint analysis of FBVMs and MBVMs. Hence, it was imperative to coordinate new research in a modern economy that encompassed both the FBVMs and MBVMs, that is what this dissertation provided. Still, based on the previous research, the succeeding ascendent models' performance ranking was inferred and hypothesised: MBVM, DDM, DCF and RIVM. Additionally, the influence of R&D expenditure was considered, and a correlated hypothesis asseverating that value estimates are more reliable for companies with zero or the lowest R&D expenditure was established.

The aforementioned hypotheses were scrutinized in a large sample analysis with an observation period from 2005 to 2015 that comprised 2,856 observations of U.S. public companies. They were evaluated based on three performance measures – bias, accuracy and explainability – by employing t-tests, Wilcoxon signed-rank tests and OLS regressions. The analysis concluded that the MBVM utilizing one-year ahead consensus forecasted earnings as a value driver performed best in all performance measures, followed by the RIVM. The DDM and DCF had inferior performances and sometimes they alternated their order of superiority, but it was feasible to infer that the DCF value estimates outperformed the DDM value estimates in bias, accuracy and explainability. Overall, the large sample analysis depicted the following ascendent ranking of performance: DDM, DCF, RIVM and MBVM. Regarding the R&D investigation, the FBVMs performed best in the low R&D subsample, while the MBVM performed best in the high R&D subsample. Nevertheless, the models' performance ranking of the main analysis prevailed unchanged in both R&D subsamples. Subsequently, a sensitivity analysis was conducted to determine the robustness of the models' valuations to the required assumptions. Indeed, it was evidenced that the models' performance ranking was robust to variations in the critical assumptions, except when the market risk premium was low, because the least sensitive model, the DDM, outperformed the other FBVMs. The sensitivity analysis also revealed that the DCF was the most vulnerable model to assumptions' alterations.

Altogether, the MBVM was the model with the best performance in the entirety of the large sample analysis. This superiority is assumed to be caused by the lower level of assumptions required by the MBVM in conjunction with the model's propensity to capture the market sentiment. However, this supremacy refuted the relevant literature, as the few previous researchers that jointly analysed the FBVMs and MBVMs inferred that the FBVMs had superior performance over MBVMs. Within the FBVMs group, the large sample analysis delineated that the RIVM outperformed the DCF and DDM, which is congruous with Francis et al. (2000) and several other authors that examined solely the FBVMs faction.

In the last section of the dissertation, to test the findings of the large sample analysis, two-sell side equity analyst reports from Morgan Stanley and RBC Capital Markets were investigated for the individual case of The Walt

Disney Company (NYSE: DIS). In harmony with the above-mentioned results, the equity analysts that produced both reports seemed to prefer the MBVM over the FBVMs for their recommendations, since they solely applied the MBVM. Therefore, although this evidence must not be generalized because analysts might alter their preferences according to the company and industry, the MBVM superiority was made clear either in the large sample analysis as in the small sample analysis for Disney.

However, it must be considered that these findings are restricted to the sample selection criteria. In concrete, the large sample analysis was limited to U.S. companies that were not from the financial and utility industries and that had positive earnings and cash flows, which removed almost all the start-up companies from the dataset. Hence, the discussed findings may not be representative of all companies. Moreover, the analysis assumed several assumptions that were necessary to implement the valuation models, and although the sensitivity analysis depicted that the findings were robust to alterations in the assumptions, these assumptions are not faithfulness because they depend on the current economic conditions at the moment of the valuation.

Therefore, since the start-ups, financial and utility companies were left out of the analysis (as suggested by a large part of the literature), the performance of the equity valuation models for these companies is worth analysing. Additional valuation procedures, as the net asset value, should also be included. As proposed by Courteau et al. (2006), another interesting research question is how a hybrid valuation approach applying the two best performer models, the MBVM and RIVM, would result. Furthermore, a comprehensive analysis of how the valuation models performed during the financial crises and an analysis comprising not only U.S. companies would also be valuable.

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