Equity Valuation Using Accounting Numbers in High and Low Intangible-Intensive Industries

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Abstract

Recent scandals in companies such as Enron, WorldCom or Tesco have become practical solid examples of accounting manipulation and have been disrupting the accountancy field. As a consequence, there has been a regular reinforcement regarding the practical use of accounting numbers. Equity valuation using accounting numbers plays a vital responsibility in both finance and accounting areas, grounding on the use and comparison of valuation models' performance.

This dissertation aims to explore the association between high and low intangible-intensive industries as well as the performance of accounting-based valuation models. After assessing not only stock- but also flow-based models across the two industries, results reveal a superior performance of the former models for low intangible-intensive industries while flow-based models disclose superior stock price predictions for high intangible-intensive industries. In complement, an analysis of the valuation techniques applied in analysts' reports demonstrates that marked multiples are usually the preferred methodology for equity research analysts to value companies.

Key Words: Intangible assets, high/low intangible-intensive industries, stock-based models, flow-based models, valuation errors, P/E, RIVM, AEGM, analysts

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IV Notations and Abbreviations

AEGM	Abnormal earnings growth valuation model
DCF	Discounted cash flow
DDM	Dividend discount model
DFCFM	Discounted free cash flow model
e.g.	Example given
E&P	Energy and petroleum
EPS	Earnings per share
EV	Enterprise value
EVA	Economic value added
GAAP	Generally accepted accounting principles
I/B/E/S	Institutional brokers' estimation system
IAS	International accounting standards
IFRS	International financial reporting standards
IPO	Initial public offering
LBO	Leverage buyout
NOPAT	Net operating profit after tax
M&M	Modigliani and Miller
Max	Maximum value
MDFY1/2	1 and 2 year-ahead forecast earnings
Min	Minimum value
NAV	Net asset value
P/E	Price earnings ratio
P1	1st percentile
P99	99th percentile
PLC	Public limited company
Q1	1st quartile
Q3	3rd quartile
R&D	Research and development
RIVM	Residual Income Valuation Model
SD	Standard Deviation
SIC	Standard Industry Classification
SEO	Seasoned equity offerings

SSA	Sub-sample A
SSB	Sub-sample B
TV	Terminal value
UK	United Kingdom

Chapter 1

Introduction

1.1 Background and Motivation to Research

Presently, terms as ‘the new economy’ and ‘intangible assets’ are powerfully connected. Intangible assets are becoming extremely important to the continued growth and development of the modern economy and well being of citizens.

International Accounting Standards (IAS) defines an asset as: a resource controlled by a firm as a result of past events from which future economic benefits are expected to flow to the entity in the future. According to Constantin *et al*. (1994) this asset category can still be separated in tangible or intangible, included in the balance sheet or not, and internally or externally created (Srivastava *et al*., 1998).

Although no consensus has yet been reached for the definition of an intangible asset, it can be expressed as an identifiable, non-monetary asset, lacking physical substance (Stolowy and Cazavan, 2001). For Wyatt (2005) and Lev (2004), examples of intangible assets include patents, trademarks, brands, licenses, technology, employee training, know-how, skilled workforces, and customer loyalty, amongst others.

The continuing transition to a more knowledge-based and technology intensive economy is causing intangible assets to be essential to preserve firm’s competitive position and to their value creation process (Holland, 2001; Lev, 2001; Sullivan and Sullivan, 2000; and Sveiby, 1997).

1.2 The Research Problem

If, as intelligible by the former section, intangibles are becoming so indispensable, they need to be correctly treated and formalised (Vance, 2001). The opposite will create unbiased and unfair results of firms’ performance (Cañibano *et al.* 1999).

Once the source of economic value is also the wealth creation of intangible assets, firms are increasing the need to make investments associated with this assets’ class (Cañibano *et al.* 1999). However, the limited accounting criteria related to the recognition of assets and their valuation leads to uncovered investments in the balance sheet. Therefore, the issue of financial statements not being able to reflect complete information of companies' financial position, providing reliable but not relevant value estimations, is being subject to debate (Cañibano *et al*., 2000).

1.3 Outline

Based on the topic that intangible assets are difficult to be perfectly measured, even though reflecting superior growth opportunities and earnings for companies, this study focus on the examination of equity valuation models' performance across high and low intangible-intensive industries. The main purpose is to compare models' results and evaluate whether the primary differences between the two industry groups considerably influence the performance of valuation techniques.

A large sample analysis will determine the valuation of both high and low intangible-intensive industries using accounting-based valuation models to, first, identify similarities and differences across industries and, second, to conclude whether (or not) there is a better valuation model for each group, reflecting lower valuation errors and, consequently, superior estimates. Next, a small sample analysis will assess the valuation approaches used by specialists to value both industries.

The study is structure as follows: the next chapter presents the main literature concerning equity valuation using accounting-based valuation models. Chapter 3 identifies and examines the results of the large sample analysis. Chapter 4 encompasses a small sample of analysts' reports, evaluating the chosen valuation techniques, forecast horizons and recommendations. In addition, it connects specific firms' characteristics with both industry samples. Finally, chapter 5 concludes the study with a summary of the major results and comments on the fields for further research.

Chapter 2

Review of Literature in Equity Valuation

2.1 Introduction

Equity valuation can shortly be defined as the task of forecasting the present value of the stream of expected payoffs to shareholders (Lee, 1999). Mostly at any level it can be implied that every business decision comprises valuation. On one hand, within the firm, capital budgeting and strategic planning involve the deliberation of the impact a project can have in firm value and how can value be subject to a set of actions, respectively. On the other hand, outside the firm, analysts resort to valuation so as to reinforce their ratings decisions while delivering forecast of value of target companies and the synergies that can be produced (Palepu *et al*., 1999).

In practice, equity valuation encompasses diverse valuation models. Nowadays, according to Damodaran (2002) and (2007) the main valuation models range from absolute valuation, relative valuation, returns based valuation and, finally to contingent claim valuation.

The following section will start with a brief reflection regarding the informational content of financial statements. The main objective is to introduce a more complex discussion of the different accounting-based valuation models and present the body of literature served as for the theoretical grounding of this study.

2.2 Usefulness of Accounting Income Numbers

According to Lee (1999), valuation is as much as an 'art' as it is a 'science'. It comprises looking into an uncertain future, and making what can be referred as an 'educated guess'. Complete objectivity is hard to achieve. Lee enforces, as a key concept to valuation, the helpfulness of information in order to estimate value. Therefore, reported accounting numbers in addition to other material, provide a comprehensive basis of information on a firm. In published financial statements, earnings are believed to be the primary information item available. Many equity valuation models share the same explanatory variable - expected earnings. Accordingly, the variable provides an adequate measure of value (Burgstahler and Dichev, 1997).

The content of income numbers can be analysed by testing how stock prices reproduce the flow of information. Ball and Brown (1968) refer that, when reported income distinguishes itself from expected income, information present in annual income figures seems to be especially useful to investors and highly linked to stock price. They limit the idea of earnings as a useful measure due to the fact that annual reports are not timely medium and, instead, their content is captured by more prompt media[1].

2.3 Accounting-Based Valuation Models

The wide number of accounting-based valuation models can essentially be distinguished into two main approaches – the stock-based and flow-based. While the latter depends on a diverse amount of estimated inputs, the former does not.

The next section introduces the central perspectives concerning business valuation and summaries five accounting-based valuation models, their pros and cons, relation to other models and implementation issues.

2.3.1 Business-Valuation Perspectives

Valuation models can be structured in two ways. The first – equity perspective[2] - values straight the equity of the firm; once this is normally the variable analysts are interested in estimating. It distinguishes the capital provided by shareholders and debt holders. The second – entity perspective[3] - values firms´ assets, which corresponds to valuing the claims equity and valuing the net debt and to remove the value of net debt. Theoretically, both approaches should generate the same values (Palepu *et. al*, 1999).

Under the equity perspective, the reporting entity is supposed to have no substance of its own separate from that of its proprietors or owners. Consequently, financial reporting from the equity perspective comprises reporting on the assets of the owners (Financial Accounting Standards Board, 2008).

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[1] Inclusion of interim reports
[2] Referred also as proprietary perspective
[3] Referred also as enterprise perspective

The accounting equation for this perspective equals (Financial Accounting Standards Board, 2008):

$$Assets - Liabilities = Equity \iff Net\ Assets = Equity \quad (1)$$

For the entity perspective, the accounting equation is the following (Financial Accounting Standards Board, 2008):

$$Assets = Creditor\ Equities + Owner\ Equities \quad (2)$$

or

$$Assets = Creditor\ Claims + Owner\ Claims \quad (3)$$

or

$$Assets = Claims \quad (4)$$

While the equity perspective makes a distinction between the different sources of capital, the entity perspective ignores them totally. The latter does not suffer so much from financing differences and allows for a better value estimate, since managers' financing decisions do not interfere. When differences in accounting affect entity valuations or valuations are less meaningful, this approach is clearly preferable. Furthermore, the equity perspective tends to dominate the entity perspective due to the weight it places on equity investment and stock markets. The downside of equity-based value estimates is the link with firm-specific financing decisions, which reduces the usefulness of a comparison across firms.

2.3.2 Stock-Based Valuation Models

Stock-based valuation models, specifically, multiples-based models, contrast with flow-based models once the first does not comprise a multi-year forecasts of a series of parameters such as earnings, growth, discount rates and others (Palepu *et. al,* 1999).

Market-multiples´ models investigate the proximity to stock prices of valuations generated by multiplying a value driver by the corresponding multiple, with the multiple being obtained from the ratio of stock price to the value driver for a group of comparable firms (Liu *et al*., 2002). Multiples is an well-liked method in equity valuation (Carter and

Van Auken, 1990) due to their simplicity in comprehension and easiness in communication (Liu *et al*., 2002). Additionally, it is employed not only by analysts but also by investment bankers, IPOs, LBOs, SEOs and other merger and acquisition transactions (Bhojraj and Lee, 2002).

Under the stock-based valuation approach, analysts trust on the market to start the task of forecasting both short- and long-term profitability and growth as well as their repercussions in the “comparable” firms’ values. Since there is a reflection of the market, the value should be considered relative and intrinsic (Palepu *et al*. 2000).

In summary, valuation using multiples involve the following steps: First, identify comparable companies, which comprise analogous operations when compared to those of the target firm whose value is being calculated and identify and select value drivers (e.g., earnings, cash flows, sales,book assets, book equity). Second, calculate the benchmark multiple from comparable firms and then, third, apply this benchmark multiple to the performance or value measure of the firm being analysed (Palepu *et al*. 2000).

The main assumptions of this model are: (1) future cash flows of comparable firms are similar to those of the target, (2) the risk profiles of comparable firms are similar to the target and (3) the value driver is proportional to value.

The general method for multiple-valuation can be written as:

$$V_i = VD_i \times Benchmark\ Multiple\ (\theta_i) \qquad (5)$$

Where $V_i$is the value estimated for firm$i$, VD_isymbolizes the value driver (where$VD_i > 0$) and θ_i reflects the set of comparable firms for firm i.

In conformity with section 2.2.1, there are two fundamental perspectives that can be applied to the different models. The multiple-based valuation model is not an exception, either equity or entity values can be estimated. For the first case, VD_i is an equity value driver (e.g. Net Income) while for the second case, VD_i represents an entity value driver (e.g. NOPAT).

2.3.2.1 Selecting Comparable Firms

Although, on the surface, using multiples appears to be very simple and straightforward, the identification of ‘comparable’ firms is often quite difficult due to its nature as a valuation heuristic. The best case scenario possible when applying price multiples is the one involving firms with similar operating and financial businesses, resulting in companies within the same industry being the most desirable candidates. Nevertheless, even industries that are strictly defined present difficulties when finding multiples for similar companies (Palepu *et al*. 2000). As Liu *et al.* (2002) argue, firms sharing the same industry reveal differences regarding strategies, profitability and goals, originating comparability issues.

Two solutions can be implemented in order to solve some of these issues. First, an average across all firms in the industry can be applied to ‘cancel out’ diverse sources of noncomparability. The second solution is to focus only on the most similar companies, which share the same industry (Palepu *et al*., 2000; Boatsman and Baskin, 1981).

An important study associated with comparables is carried by Alford (1992), who concludes that valuations using comparables chosen by their 3-digit SIC code is a good proxy for industry specific characteristics.

2.3.2.2 Calculating the Benchmark Multiple

Complementing the implementation issue of comparables is the issue that preferable applied drivers in multiples are more volatile than equity prices, resulting in comparable firm multiples being quite dispersed (Fernández, 2002). Thus, a statistic estimator able to summarise a benchmark multiple is compulsory. The most popular are presented next:

- $\text{Mean (arithmetic average)} = \frac{1}{n}\sum_{j=1}^{n}\frac{Pj}{VDj}$ *(6)*
- $\text{Median} = \textit{midpoint of observed values}'\textit{ frequency distribution}$ *(7)*
- $\text{Weighted average} = \sum_{j=1}^{n}\frac{VDj}{\sum_{i=1}^{n}VDi}\times\frac{Pj}{VDj} = \frac{\sum_{j=1}^{n}Pj}{\sum_{j=1}^{n}VDj}$ *(8)*
- $\text{Harmonic mean} = \frac{1}{\frac{1}{n}\sum_{j=1}^{n}\frac{VDj}{Pj}}$ *(9)*

Where VD_j denotes the value driver and P_j the observed price for the j^{th} comparator firm.

Baker and Ruback (1999) defend that the harmonic mean *(9)* use delivers superior valuation performance compared to the other three outlined estimators (*6,7* and *8*). In fact, the authors point out that multiples resulting from the simple mean tend to overvalue. The mean-based estimation will always return a higher number than the harmonic mean value, which yields less upward-biased estimates.

2.3.2.3 Selecting Value Drivers

Value drivers are an important input for multiple valuations and should reflect a proper proxy for firm's performance. Forecasted earnings are the most common used value driver due to their high informational content. Nevertheless, their selection depends on the company and the industry they are assigned to. Multiples using forecasted earnings as value driver have a better performance, with valuation results being improved with the forecast horizon (Liu *et al*., 2002 and Fernández, 2002).

Liu *et al*. (2002) in their study find that multiples using estimated earnings as value drivers outperform multiples using reported earnings across different GAAP jurisdictions. Additionally, Liu *et al*. (2007) reinforces the popularity of P/E-multiples by showing that valuations based on earnings multiples are preferable for the majority of companies due to its stronger accuracy compared to value estimates from cash flow multiples.

2.3.3 Flow-Based Valuation Models

The following flow-based valuation techniques presented ground on the notion that the market value of a share is the discounted value of the expected future payoffs generated by the share. Although payoffs can diverge, under a set of conditions, models produce theoretically correspondent measures of intrinsic value.

2.3.3.1 Dividend Discount Model (DDM)

Valuations models derive, more or less obviously, from the DDM attributed to Williams (1938), making it a reference for almost all valuation techniques (Barker, 2001).

Dividends are equivalent to the cash flows distributed to shareholders and reported in the cash flow statement (Penman, 2007). The main supposition lies on the fact that the market value of equity capital is defined as the sum of discounted future net cash flows. DDM (equity version) estimates the value of a stock by computing the present value of the expected future cash dividends (Ross *et al*., 2008). Thus:

Value of the equity = Present value of expected dividends

The subsequent formula states the dividend discount model:

$$V_F^{DIV} = \sum_{\tau=1}^{T} \frac{DIV_t}{(1+r_E)^t} \tag{10}$$

Where DIV_t denotes the dividends and r_E the equity cost of capital.

The DDM is the simplest model used in equity valuation and it is also the most essential and important flow-based model. DDM preferences from investors have to do with the forecasting task, which is very straightforward and easy, assumed stable dividend policies (Brealey *et. al* 2005; Penman, 2008). However, the main limitation is the requirement that dividend forecasts to infinity. Copeland *et al.* (2008), in order to deal with the problem, suggest splitting business value into two periods, during and after the explicit forecasting period. The value beyond the forecast horizon is a terminal value featuring a continuous growth rate.

Other limitation is DDM association with Modigliani and Miller's (1961) dividend irrelevance proposition. Many researchers do not agree with M&M proposition and state the dividend's contribution in valuation. Both Walter (1956) and Black and Scholes (1974) concluded that a change in dividend policy affects stock price. Besides, Fisher (1961) explains that dividend and profit have analogous effects on share prices.

2.3.3.2 Discounted Free Cash Flow Model (DFCFM)

The discounted free cash flow model is based on the DDM, with the difference being that it replaces free cash flows for dividends since it assumes free cash flows to be a better demonstration of value added over a short horizon.

Free cash flows equal the cash available to the firm's providers of capital after all required investments. Algebraically it can be represented as (Francis, *et al.* 2000):

$$\mathrm{FCF_t} = (\mathrm{Sales_t} - \mathrm{OPEXP_t} - \mathrm{DEPEXP_t})(1-\tau) + \mathrm{DEPEXP_t} - \Delta\mathrm{WC_t} - \mathrm{CAPEXP_t} \tag{11}$$

Where $\mathrm{Sales_t}$ equals sales revenues for year t; $\mathrm{OPEXP_t}$ denotes operating expenses for year t; $\mathrm{DEPEXP_t}$ expresses depreciation expense for year t; $\Delta\mathrm{WC_t}$ represents the change on working capital in year t and $\mathrm{CAPEXP_t}$ is equivalent to capital expenditures in year t.

Thus, the final model is expressed as the following (Francis *et. al*, 2000):

$$V_F^{FCF} = \sum_{T=1}^{T} \frac{FCF}{(1+WACC)^t} + ECMS_F + D_F + PS_F \qquad (12)$$

Where $ECMS_F$ is equal to the excess cash and marketable securities at time t;$D_F$is the market value of the debt at time t and PS_F illustrates the market value of preferred stock at time t.

With:

$$\text{WACC} = w_d\,(1-\tau)r_d + w_{PS}r_{PS} + w_E\,r_E \qquad (13)$$

Where WACC expresses the weighted average cost of capital; r_d equals the cost of debt; r_{PS} denotes the cost of preferred stock; w_d is the proportion of debt in target capital structure; w_{PS} is equivalent to the proportion of preferred stock in target capital structure; w_E is the proportion of equity in target capital structure and τ the corporate tax rate.

The main model's limitation is the fact that the free cash flow does not really add value in operations. It confuses investments with the payoffs from investments since it is somewhat an investment or a liquidation concept (Penman, 2007).

Another practical problem is the fact that free cash flows, in contrast to earnings, are not exactly what analysts forecast.

2.3.3.3 Residual Income Valuation Model (RIVM)

Residual income, or abnormal earnings, plays a protuberant role in equity valuation, being used as a measure of performance (O'Hanlon, 2002). According to Ohlson (1995), residual earnings are equal to accounting earnings less a cost of capital based on the opening book value of equity *(14).* This meaning is analogous to the economic value added (EVA) concept and, based on Lee (1996), the development of the RIV model corresponds to the EVA paradigm.

The traditional RIV model approach, based on an equity perspective, rests on the assumptions that company's value equals the present value of expected future dividends and both earnings and book value forecasts result from a Clean Surplus Relationship (CSR). According to this relationship, *(15)* earnings equal the change in book value of equity plus dividends net of capital (O'Hanlon, 2009). Thus, the intuition behind the derivation of the residual income model is to exactly use book value and forecasted future earnings (premium) to back out dividends using the clean surplus relation *(16)*.[4]

$$RI_t^e = NI_t - k_e \times BVE_{t-1} \tag{14}$$

$$BVE_t - BVE_{t-1} = NI_t - DIV_t \tag{15}$$

$$V_t^e = BVE_t + \sum_{\tau=1}^{\infty} \frac{E_t[RI_{t+\tau}^e]}{(1+k_e)^\tau} \tag{16}$$

When compared to market multiples, the RIVM is able to address some of the model's implementation issues, essentially due to its easiness in obtaining the computations of equity values, by focusing on observed book values, return on equity and equity cost of capital (Bryan *et al*, 2001). When comparing the RIVM final values with extra available estimations from the dividend discount and cash flow models, empirical studies conclude that residual-earnings-based value estimates are superior. The reasons stated include (1) the model's support in book values, explaining a larger proportion of intrinsic value and (2) the use of more precise earnings forecasts (Courteau *et al*. 2007).

Accounting discretion and accounting conservatism have been explained as two of the main limitations of accounting-based valuation models although they do not seem to have any impact on the reliability of residual earnings estimates (Francis *et. al*, 2000).

Along the last years, researchers have been studying the usefulness of the RIVM value estimates. By comparing the value estimates of the three different (DD, DFCF and RIV) models, RIVM shows to be the most accurate and the one explaining more variation in stock price (Penman and Sougiannis, 1998; Francis *et al.,* 2000). Besides, researchers also found that earnings approaches do not have a good performance for high numbers of both price-to-earnings and price-to-book. In this case, terminal value calculations are relevant for valuation.

Among several researchers, the RIV model is preferred as a superior technique for valuation within finite horizons (Penman and Sougiannis, 1998 and Francis *et al*., 2000) However, the RIVM and the DCFM have equal value estimates when complete pro-forma statements are available (Lundholm and O'Keefe, 2001).

[4]Derivation based on the equity perspective and entity perspective in appendix

The limitations of the RIV model are highlighted by Ohlson and Juetter-Nauroth (2005), stating the model's dependency on the clean surplus relationship and its anchorage in book values. First, the application of the RIVM requires a clean surplus relationship on a per share basis. Second, it is not possible to avoid the per share issue, by applying the RIVM on a total dollar value basis. Concluding, Ohlson (2005) claims the RIVM inability to generate per-share value estimates if M&M restrictions are not re-introduced.

Consequently, Ohlson and Juettner-Nauroth (2005) created the abnormal earnings growth model (AEGM) through the expansion of RIVM, by relating a firm's share price to its capitalised next period earnings, its short and long term earnings growth and cost of equity capital.

2.3.3.4 Abnormal Earnings Growth Model (AEGM)

In accordance with the RIV model, the AEG model, also known as Ohlson/Juettner-Nauroth (OJ) model, conceptually grounds on the same mathematical structure as the RIVM. In addition, it starts from the present value of future dividends [5](Penman, 2008; O'Hanlon, 2009). Ohlson (2005), the residual earnings valuation framework developer, forecasts an actual replacement of the RIVM by the AEGM, since the former is aligned with analysts' focus on earnings. The AEGM model, on the contrary, defines intrinsic value of equity as capitalised, next-period earnings plus the present value of capitalised, forecasted abnormal earnings growth in succeeding periods *(12)* (Ohlson and Juetter-Nauroth, 2005). Abnormal earnings growth is defined as the difference between periodic earnings change and a normal return on previous-period earnings *(13)* (Ohlson and Juetter-Nauroth, 2005).

$$V_t^e = \frac{E_t\,[NI_{t+1}]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_t[z_{t+\tau}]}{(1+k_e)^{\tau}} \qquad (17)$$

$$z_t = \frac{1}{k_e}[\Delta NI_{t+1} - k_e\,(NI_t - DIV_t)] \qquad (18)$$

The AEGM is able to overcome shortcomings of the RIVM since it relies on capitalised, next period earnings. Thus, the model expresses its premium as successive increments in expected earnings adjusted for dividends (O'Hanlon, 2009). It does not demand an anchor on book values and does not rely on the notion of a CSR. Thus, a valuation per-share on a

[5]Derivation in appendix

total dollar basis is possible and capital transactions' undesirable effects are disregarded (Ohlson, 2005).

The practitioner's advantage side is the model's focus on earnings, the main catalyst for value creation. The idea underlined is that ex-ante capitalized earnings approximate market value more closely than book values (Ohlson, 2005).

2.5 Discussion of Valuation Model Performance

In accordance to Demirakos et al. (2004), the discussion between academics and practitioners , with regard to valuation models, remains. If multi-period valuation models are theoretically superior there is a weak practitioners' application.

Gleason et al. (2008) enlarged the number of arguments in favour of flow-based valuation models. According to the authors, the application of flow-based valuation models by analysts brings a significantly improved accuracy in the calculation of price targets. This fact enables to highlight the quality deterioration when the calculation is based on valuation heuristics as well as on inaccurate earnings forecasts.

Although the usual academic position, practitioners tend to apply stock-based models. Valuation heuristics are normally applied as a bottom line for firm valuation and combined, if necessary, with more complex models (Barker, 1999).

Courteau *et al.* (2007) shows that flow-based models performance are superior to multiples, regarding pricing and return-prediction. Nonetheless, they provide empirical evidence of companies' analysis improvement by combining a multiples valuation with flow-based valuation frameworks.

In contrast, Imam *et al*. (2008) claims that practitioners have a preference for flow-based valuation models, highlighting the models' preference role as a key valuation technique in analysts reports, when compared to accrual-based models. However, valuation accuracy is not improved by cash flow-based valuation (Imam *et al*., 2008). Sougiannis and Yaekura (2001), Fernández (2002), and Imam *et al.* (2008) highlight the fact that multiples are extensively used when combined with more sophisticated frameworks.

Apart from stock- or flow-based, accounting-based valuation models are subject to inaccuracies primarily attributed to: accounting measurement errors; quality of earnings forecasts; specifications; and the efficient market hypothesis.

Tasker (1998) states that the effectiveness of accounting rules performance across industries affects accounting-based valuation profoundly. The most evident source of valuation errors and accounting-based valuation models' performance are endorsed to the inferiority of GAAP earnings. Particularly, losing firms, even though demonstrating high growth and/or high R&D-expenses, they are jeopardized by conservative accounting rules once they reduce book values and reported earnings' informational content. Sougiannis and Yaekura (2000) suggest that applying longer forecast horizons can overcome current losses and R&D-expenses.

2.6 Concluding Remarks

The previous section comprised the main literature and theoretical foundation of accounting-based equity valuation. Flow-based valuation models seem to show superiority compared to stock-based valuation models, specifically, market multiples. Nevertheless, practitioners frequently decide to use this last model in valuations.

The following section will employ part of the valuation models presented to a sample of high and low-intensive intangible firms. The objective is to conclude if valuation performance across certain accounting-based models is subjective to company's asset structure.

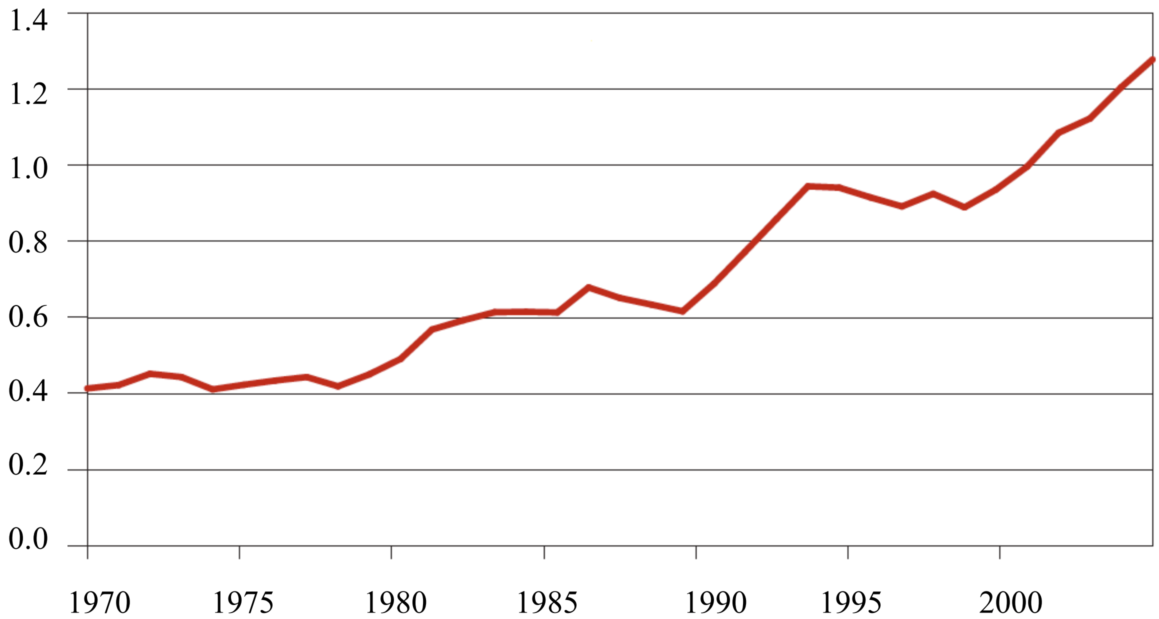
Chapter 3

Large Sample Analysis

As outlined in chapter 1, accounting numbers do not always reflect fair value at a specific moment in time. Specifically, companies with a high level of investments, whether in brand names or in R&D and advertising, do not have this amount of value recognised in the balance sheet.

Nowadays, consumers are usually more willing to buy advertised brands due to a superior sense of trust and brand awareness. Thus, companies are currently spending money on the intangibles´ asset class in order to realize future revenue potential (Figure 1).

Figure 1 – Intangible to tangible ratio growth in the UK



Source: HMT (2007) Intangible Investment and Britain's Productivity: Working

When a company builds a plant or purchases equipment, the asset is capitalised on the balance sheet and depreciated over time. Conversely, when a company creates an intangible asset, such as a brand name or patent, the entire outlay must be expensed immediately. For firms with significant intangible assets, such as technology companies and pharmaceuticals, failure to recognize intangible assets can lead to a significant underestimation of a company's invested capital and, thus, overstate return on invested capital (ROIC) (Koller *et al*., 2005).

3.1 Research Question and Literature

According to Hall (2001), the valuation effect of intangible assets in firms' market value is more important than that of tangible assets.

Recent research by Amir and Lev (1996) has achieved a mark in the area of intangibles. They evaluate the roles of accounting and nonfinancial information in the valuation of cellular phone companies. Results reveal that financial information is largely irrelevant in valuing U.S. cellular phone companies once accounting requires the immediate expense of customer acquisition costs.

As mentioned on section 2.3, valuation models should give the same or similar intrinsic value. Nevertheless, some models can indeed outperform others according to different assumptions and input variables. Similarly, industry characteristics matters, in fact, specific models result in superior performances in particular industries.

The large sample analysis section of the study aims to evaluate if the use of disparate valuations models give different results according to different industry groups. By having two distinctive groups, questioning whether (or not) the valuation model applied is different reveals to be a valuable study. In addition, it is pertinent to evaluate the performance of different models for each of the underlying groups, separately. The main hypothesis of the analysis consists on the fact that differences in earnings patterns and industry characteristics influence models' valuation performance. Thus, a firm's industry characteristic is able to determine the capacity of a model to capture firm value. The study of models' performance is based on the accuracy and bias of value estimates.

3.2 Data and Sample Selection

The original data used to perform the large sample analysis is grounded on values from the I/B/E/S and COMPUSTAT databases and includes 11.493 observations of annual firms' accounting data, share prices and analysts forecasts for U.S. public firms between 2005 and 2010.

COMPUSTAT collects accounting data, among others, directly from firms' financial statements as of 31st December and I/B/E/S gathers and summarises analysts' forecasts from a broad cross-section of equity analysts as of 15th April.

The sampling selection process described in table 1 excludes from the original sample provided observations with missing or negative 1-year, 2-year and long-term I/B/E/S earnings forecasts and negative values of earnings per share as well as extreme (low and high) share prices ($2<P<300$). The objective is to guarantee that all valuation models result in reasonable results. Afterwards, observations not belonging to major SIC code groups were excluded from the original sample. The criteria assents on the rational that industries with less than 0.75% frequency distribution of observations do not reflect and are not representative of an industry class.

The selection of high vis-à-vis low intangible-intensive industries is based on a study by Collins *et al.* (1997), which defines firms as intangible intensive when their production function likely include large amounts of unrecorded intangibles.

The grounding literature is, again, based on Collins *et al.* (1997), where intangible-intensive firms belong to the two-digit SIC codes: 48 (electronic components and accessories), 73 (business services), 87 (engineering, accounting, R&D and management related services); and three-digit SIC codes: 282 (plastics and synthetic materials), 283(drugs), and 357 (computer and office equipment). This study permits to extrapolate the high intangible-intensive industries as fitting to the previously mentioned SIC codes. The two-digit SIC codes (48, 73 and 87) were amplified to include all the three-digit SIC codes, once these provide better performance results (Alford, 1992).The low intangible-intensive industries are the remaining SICs not belonging to the high intangible-intensive industry sample (Collins *et al*., 1997).

Furthermore, it is necessary to note that, in this study, intangible intensity does not refer only to the presence of large amounts of recorded intangibles once the research question also tries to capture unrecorded intangibles (Collins *et al*., 1997).

Table 1 – Sample selection (untrimmed data)

Observations of U.S. public firms between 2005 and 2010	11493
(-) Observations with missing mean and median consensus forecasts (E1,E2 and LTG)	3178
(-) Observations with negative variables giving negative or zero valuation results	1042
(-) Observations with extreme share prices	68
(=) Subtotal	7205
(-) Industries not belonging to major SIC3 code groups	2917
Subtotal - pooled sample	4288
Sub-sample A (high intensive intangible industries)	1916
Sub-sample B (low intensive intangible industries)	2372

Table 2 describes the sample selection process regarding the untrimmed data. The first subtotal is obtained by retaining the non-missing mean and median consensus forecasts for long-term growth (LGT), one- (E1) and two-year-ahead (E2) forecasts. In addition, the negative variables are excluded as well as the missing and extreme share prices available. To determine the pooled sample, industries with less than 0.75% frequency distribution of observations are also excluded. Finally, based on Collins *et al*. (1997) the selection of high- and low intangible-intensive industries is made.

The selection process generates three final outputs. This selection enables an overall analysis of specific industry characteristic groups by focusing on the comparison of valuation accuracy, valuation bias, and explanatory power both on an aggregate and disaggregated level.

3.3 Research Design

In order to compare accounting-based valuation models and to conclude their performance across high and low intangible-intensive industries, the empirical analysis section comprises three main valuation models; one stock-flow based model represented by the P/E multiple[6] and two flow-based valuation models reflected by the RIVM and AEGM.

Valuation model performance is consistent with the methodology applied by Lie and Lie (2002), Liu *et al.* (2002) and Corteau *et al.* (2007). The rational is based on the argument that valuation errors reflect reasonable measures of model's accuracy and bias. Valuation bias is measured by signed valuation errors *(19)* and represents the model's tendency to under- or overvalue as a percentage of price at valuation date.

$$Signed\ valuation\ error_t = \frac{VE_t - P_t}{P_t} \qquad (19)$$

Valuation accuracy is measured by absolute valuation errors *(20)* and represents the percentage of price at valuation date not incorporated by the value estimate.

[6] From now on abbreviated as P/E

$$Absolute\ valuation\ error_t = \frac{|VE_t - P_t|}{P_t} \quad (20)$$

Where VE_t reflects the value estimate and P_t the price at valuation date.

3.3.1 Stock-Based Valuation

The details of the P/E multiple, as well as the assumptions and steps required to derive the model, are presented on this stock-based valuation section.

3.3.1.1 Value Driver Selection

The 1- and 2-year-ahead median earnings forecasts provided by I/B/E/S are used in order to derive two different examples of the P/E multiple. The decision on the median earnings forecasts are based on the arguments made by Frankel and Lee (1998) and Francis *et al.* (2000), stating the use of core earnings as providing a better valuation performance. The forecast horizon extension allows as with Liu *et al.* (2002, 2007), the improvement of valuation performance.

3.3.1.2 Comparable Firms Selection

This section presents the selection of comparables in the multiples valuation model, essentially following Alford (1992). Industries matching identify comparable firms and are chosen in line with their three-digit SIC code. In accordance with Alford (1992), the three-digit SIC code provides superior results than the two-digit SIC code[7].

3.3.1.3 Benchmark Multiples

Benchmark multiples are estimated by calculating the harmonic mean of all comparables firm multiples in the three-digit SIC code, excluding the targets own valuation multiple (Liu *et al.* (2002, 2007).

3.3.2 Flow-Based Valuation

As presented before, two flow-based valuation models are applied, the RIVM and the AEGM. The RIVM considers a two-year valuation horizon and two terminal values estimates (1.5% and 3%), while the AEGM is based on a finite two-year ahead valuation horizon.

[7] Further extension to the four-digit SIC code does not provide better estimates (Alford, 1992).

Flow-based models are subject to certain assumptions reflected in their parameters. The main variables are considered next.

3.3.2.1 Cost of Capital (k)

The cost of capital reflects the premium demanded by equity investors, being an essential part of every valuation encompassing a discount method. In order to consistently compare flow-based valuation models, the estimate cost of capital is similar and constant over the valuation horizon. The cost of capital is estimated by using the capital asset pricing model (CAPM) presented below *(16):*

$$K = r_f + \beta \times r_p \tag{21}$$

Where K represents the cost of capital, r_f the risk free rate (long-term U.S. Treasury bond yield), β a constant beta-factor and r_p the market risk premium. The market risk premium is 4% based on Frankel and Lee (1998) and Lee *et al.* (1999) use of a constant market risk premium.

3.3.2.2 Earnings per Share (EPS)

So as to calculate residual earnings, the median I/B/E/S consensus earnings forecasts are applied. These earnings forecasts along with the dividend payout ratio presented next enable both a cross, model and sample, industry comparison[8].

3.3.2.3 Dividend Payout Rate

The dividend payout rate is a firm-specific parameter representing the percentage of net income distributed to investors as dividends (Copeland *et al.,* 2008; Penman, 2007). This variable is essential to be able to calculate residual earnings and is calculated using the quotient of dividends and net income before extraordinary items (Frankel and Lee (1998); Lee and Swaminathan (1999)).

3.3.2.4 Growth-Rate

For periods exceeding the valuation horizon, a terminal value is included (Barker, 2001). To approximate firm value beyond the valuation horizon, the RIVM comprehends terminal value expressions. The sensitivity of the model to long-term growth rates is

[8] Per-share basis

measured by applying two different values, 1.5% and 3% respectively.

3.4 Empirical Results

This section focuses on the empirical results of the large sample analysis, with descriptive statistics of the three samples being presented.

3.4.1 Descriptive Statistics

The descriptive statistics identified in table 2 and 3 indicate the differences between the pooled sample, sub-sample A and sub-sample B as for untrimmed and trimmed data respectively. Particularly, they present the main descriptive statistical variables to each industry. From now on, the analysis focuses on the main final output – the trimmed sample.

First, as reflected by a higher mean share price, firms in low intangible-intensive industries trade, on average, at a superior value than firms belonging to high intangible-intensive industries. Similarly, the book value per share (BVS) of sub-sample B is 1.59x the BVS of sub-sample A. The book value per share is a ratio related to the level of safety linked to each individual share after debt is paid (Carmichael *et al.,* 2007). Hence, firms belonging to low intangible-intensive industries demonstrate a larger amount of value remaining for common shareholders (lower price to book value per share mean) in comparison to high intangible-intensive industries. This superior ratio indicates a stronger expectation by investors that management will create more value for a given set of assets. Nevertheless, this ratio can be very limited. Presently, firms' create value also as a result of intangible assets, most of which are not straight forwardly incorporated in the book value.

There is a significant difference between each sub-sample mean EPS, with sub-sample B having a superior value and being, on average, more profitable than firms in high intangible-intensive industries. In addition, low intangible-intensive industries have a higher standard deviation of EPS when compared to high intangible-intensive industries. This value can be a result of the higher degree of financial leverage sub-sample B is subject to. Due to the large amount of fixed and operational costs companies with significant amounts of tangible assets have, the volatility of earnings becomes higher. In conclusion, all observed variables reveal consistency with the existing differences between the two industries.

Table 2 - Untrimmed sample descriptive statistics

Panel A: Pooled Sample	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	4288	29.9836	24.4800	24.0817	2.0500	13.7400	39.6200	295.9100
EPS excluding extraordinary items (EPS)	4288	1.2881	0.9800	2.1508	-26.6000	0.3400	1.9700	31.4612
Book value per share (BVPS)	4288	3.7951	2.7028	3.6859	0.0013	1.0970	5.3907	33.2882
Median of 1-year ahead EPS forecast (EPS1)	4288	1.6819	1.2700	1.5971	0.0100	0.6100	2.2300	23.0000
Median of 2-year ahead EPS forecast (EPS2)	4288	1.9839	1.5100	1.7596	0.0200	0.8100	2.5500	18.2500

Panel B: Sub-Sample A *(high intangile-intensive industries)*	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	1916	24.4116	18.5650	21.7416	2.0200	10.3950	31.9300	295.9100
EPS excluding extraordinary items (EPS)	1916	0.7738	0.5900	1.6665	-17.4300	0.1300	1.2833	15.1900
Book value per share (BVPS)	1916	8.3548	6.7610	6.9441	0.0543	3.7496	10.5695	83.1011
Median of 1-year ahead EPS forecast (EPS1)	1916	1.2060	0.8400	1.2279	0.0100	0.4200	1.5700	13.0700
Median of 2-year ahead EPS forecast (EPS2)	1916	1.4472	1.0500	1.3541	0.0200	0.5900	1.8450	14.4900

Panel C: Sub-Sample B *(low intangile-intensive industries)*	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	2372	33.3358	27.9200	24.8463	2.0500	16.1800	43.6200	284.0000
EPS excluding extraordinary items (EPS)	2372	1.5045	1.3100	2.5647	-26.6000	0.4530	2.4300	31.4612
Book value per share (BVPS)	2372	14.4366	11.9768	12.4247	0.0007	6.5555	18.8056	190.6495
Median of 1-year ahead EPS forecast (EPS1)	2372	1.9792	1.5600	1.7582	0.0100	0.8000	2.6300	23.0000
Median of 2-year ahead EPS forecast (EPS2)	2372	2.3280	1.8500	1.9272	0.0300	1.0400	3.0200	18.2500

The sample securities are for U.S. public firms between 2005 and 2010. Table 3 outlines the characteristics of the pooled sample and the two sub-samples based on the selection process as untrimmed data. Summary descriptions of the variables are on per share basis. P, EPS1 and EPS2 are taken from I/B/E/S and EPS and BVS are taken from COMPUSTAT and have been adjusted for stock splits to make them consistent with the I/B/E/S data.

Table 3 - Trimmed sample descriptive statistics

Panel A: Pooled Sample	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	3662	27.0194	23.4250	17.4649	2.8300	13.5500	37.0800	100.5600
EPS excluding extraordinary items (EPS)	3662	1.1520	0.9300	1.3319	-6.0700	0.3300	1.8300	7.7400
Book value per share (BVPS)	3662	10.7778	8.7557	7.4155	1.0525	5.0643	14.8611	39.9658
Median of 1-year ahead EPS forecast (mdfy1)	3662	1.4808	1.2000	1.1753	0.0100	0.6000	2.0500	8.4100
Median of 2-year ahead EPS forecast (mdfy2)	3662	1.7485	1.4450	1.2914	0.0300	0.7800	2.3600	12.7700

Panel B: Sub-Sample A *(high intangile-intensive industries)*	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	1646	23.4292	18.9600	16.0901	2.8300	11.3000	31.5900	96.3200
EPS excluding extraordinary items (EPS)	1646	0.8104	0.6250	1.0966	-4.6400	0.1800	1.2700	5.8300
Book value per share (BVPS)	1646	8.1347	6.8538	5.7691	1.0525	4.0296	10.3394	39.3378
Median of 1-year ahead EPS forecast (mdfy1)	1646	1.1648	0.8500	1.0120	0.0100	0.4600	1.5500	8.4100
Median of 2-year ahead EPS forecast (mdfy12)	1646	1.3931	1.0600	1.0813	0.0500	0.6400	1.8100	7.2900

Panel C: Sub-Sample B *(low intangile-intensive industries)*	n	Mean	Median	SD	Min	Q1	Q3	Max
Share Price in April (P)	2016	29.9507	26.8650	17.9920	2.8300	16.0800	39.9450	100.5600
EPS excluding extraordinary items (EPS)	2016	1.4309	1.2917	1.4382	-6.0700	0.5300	2.2200	7.7400
Book value per share (BVPS)	2016	12.9358	11.6222	7.8975	1.1549	6.5956	17.6499	39.9658
Median of 1-year ahead EPS forecast (mdfy1)	2016	1.7387	1.5000	1.2351	0.0100	0.8000	2.4000	8.4000
Median of 2-year ahead EPS forecast (mdfy2)	2016	2.0386	1.7500	1.3742	0.0300	1.0450	2.7000	12.7700

The sample securities are for U.S. public firms between 2005 and 2010. Table 3 outlines the characteristics of the pooled sample and the two sub-samples based on the sample selection process as raw and trimmed data. Summary descriptions of the variables are on per share basis. P, EPS1 and EPS2 are taken from I/B/E/S and EPS is taken from COMPUSTAT and have been adjusted for stock splits to make them consistent with the I/B/E/S data). The data provided was trimmed by 1% on both tails to exclude extreme outliers and generate robust as well as representative results.

3.4.2 Analysis of Valuation Errors

In order to properly evaluate both accuracy and bias of valuation models, valuation errors are evaluated. This section centers on evaluating signed and absolute valuation errors mentioned on the research design section (3.3). First, the descriptive statistics, as well as the statistical significance of valuation errors, are presented (3.4.2.1).

Subsequently, on section 3.4.2.2, mean and median valuation errors differences across the two sub-samples are examined. The final analysis comprises the comparison of valuation models and value estimates (3.4.2.3) and, lastly, the OLS regression (3.4.2.4).

3.4.2.1 Intra-Sample Analysis of Valuation Errors

The descriptive statistics of valuation errors for each the selected valuation models and sub-sample is summarized next.

Table 4 - Descriptive statistics of valuation errors (trimmed data)

Panel A: Pooled Sample	**n**	**Mean**	**Median**	**SD**	**Min**	**Q1**	**Q3**	**Max**
P/E Multiple (mdfy1)								
Signed Prediction Errors	3662	0.0061	-0.0253	0.4787	-0.9152	-0.3427	0.4455	7.1390
Absolute Prediction Errors	3662	0.2862	0.2291	0.3897	0.0000	0.1399	0.5255	7.1390
P/E Multiple (mdfy2)								
Signed Prediction Errors	3662	0.2963	0.1633	0.5700	-0.8622	-0.0629	0.4195	7.9015
Absolute Prediction Errors	3662	0.3901	0.2674	0.4941	0.0002	0.1143	0.3378	7.9015
RIVM (2-year / 1.5% terminal value)								
Signed Prediction Errors	3662	-0.0903	-0.1838	0.4912	-0.9745	-0.3503	0.0323	8.2108
Absolute Prediction Errors	3662	0.3381	0.2913	0.3521	0.0002	0.1413	0.4507	8.2108
RIVM (2-year / 3% terminal value)								
Signed Prediction Errors	3662	-0.0003	-0.0868	0.6281	-1.5745	-0.2911	0.1403	10.5822
Absolute Prediction Errors	3662	0.3781	0.2648	0.5208	0.0001	0.1282	0.4985	10.5822
AEGM (2-year / no terminal value)								
Signed Prediction Errors	3662	-0.2277	-0.2572	0.3272	-0.8923	-0.3940	-0.0436	5.9242
Absolute Prediction Errors	3662	0.3311	0.2577	0.2876	0.0005	0.1737	0.4658	5.9242
Panel B: Sub-Sample A *(high intangile-intensive industries)*	**n**	**Mean**	**Median**	**SD**	**Min**	**Q1**	**Q3**	**Max**
P/E Multiple (mdfy1)								
Signed Prediction Errors	1646	0.0202	-0.0685	0.5500	-0.9152	-0.3032	0.1820	7.1390
Absolute Prediction Errors	1646	0.4158	0.2846	0.4360	0.0000	0.1217	0.3773	7.1390
P/E Multiple (mdfy2)								
Signed Prediction Errors	1646	0.3913	0.2652	0.6860	-0.7224	-0.0258	0.2401	7.9015
Absolute Prediction Errors	1646	0.4947	0.3869	0.6050	0.0003	0.1210	0.3695	7.9015
RIVM (2-year / 1.5% terminal value)								
Signed Prediction Errors	1646	-0.1039	-0.2228	0.5259	-0.9745	-0.3704	0.3837	6.9211
Absolute Prediction Errors	1646	0.3905	0.2526	0.4345	0.0002	0.1313	0.0085	6.9211
RIVM (2-year / 3% terminal value)								
Signed Prediction Errors	1646	-0.0001	-0.0650	0.6499	-1.5745	-0.3054	0.1351	9.8786
Absolute Prediction Errors	1646	0.4385	0.3341	0.5341	0.0001	0.1305	0.4639	9.8786
AEGM (2-year / no terminal value)								
Signed Prediction Errors	1646	-0.2566	-0.2938	0.4999	-0.8592	-0.4063	-0.0462	5.9242
Absolute Prediction Errors	1646	0.3719	0.2948	0.3518	0.0009	0.1642	0.4042	5.9242
Panel C: Sub-Sample B *(low intangile-intensive industries)*	**n**	**Mean**	**Median**	**SD**	**Min**	**Q1**	**Q3**	**Max**
P/E Multiple (mdfy1)								
Signed Prediction Errors	2016	0.0041	0.0057	0.3733	-0.9052	-0.1775	0.1992	6.3715
Absolute Prediction Errors	2016	0.2257	0.2610	0.2640	0.0000	0.0955	0.4718	6.3715
P/E Multiple (mdfy2)								
Signed Prediction Errors	2016	0.1600	0.1624	0.3688	-0.8622	-0.1032	0.5157	5.8822
Absolute Prediction Errors	2016	0.2827	0.2234	0.3358	0.0002	0.1032	0.5303	5.8822
RIVM (2-year / 1.5% terminal value)								
Signed Prediction Errors	2016	-0.0794	-0.1535	0.4944	-0.9327	-0.3494	0.0929	8.2108
Absolute Prediction Errors	2016	0.3144	0.2607	0.3810	0.0002	0.1138	0.4160	8.2108
RIVM (2-year / 3% terminal value)								
Signed Prediction Errors	2016	-0.0038	-0.9364	0.6303	-1.1889	-0.3250	0.2791	10.5822
Absolute Prediction Errors	2016	0.3636	0.2502	0.5561	0.0002	0.1364	0.4934	10.5822
AEGM (2-year / no terminal value)								
Signed Prediction Errors	2016	-0.1953	-0.2269	0.3811	-0.8923	-0.3704	-0.0042	4.5345
Absolute Prediction Errors	2016	0.3453	0.2529	0.2789	0.0005	0.1629	0.4269	4.5345

Table 4 reports the descriptive valuation errors in all featured samples on the basis of the trimmed data shown in table 4. All models are considered, with P/E multiple denominators being the I/B/E/S one- and two-year-ahead earnings forecasts. Regarding the RIVM model, both a 1.5% and 3% terminal value are evaluated. Mean and median signed and absolute prediction errors are presented and equal to $(V_i V_E - P_{i,F}) / P_{i,F}$.

Mean and median valuation errors are tested for their statistical significance by applying parametric and non-parametric tests. Specifically, the t-test and the

Wilcoxon signed rank test are performed to test mean and median equality respectively. The results of these tests are presented in table 5 within all samples (pooled and sub-samples). A significance level of 5% is used for the hypothesis of both tests.

The hypotheses applied for the three samples in the t-test are the following:

H_0 : $Mean\ valuation\ error\ =\ 0$

H_1 : $Mean\ valuation\ error\ \neq\ 0$

Regarding the Wilcoxon signed rank test, the hypotheses tests used are stated below:

H_0 : $Median\ valuation\ error\ =\ 0$

H_1 : $Median\ valuation\ error\ \neq\ 0$

Table 5 – Intra-sample valuation accuracy and bias

Panel A: Pooled Sample	**Signed Prediction Errors**				**Absolute Prediction Errors**			
	Mean	p-value	Median	p-value	Mean	p-value	Median	p-value
P/E Multiple (mdfy1)	0.0061	0.3928	-0.0253	0.2594	0.2862	<0.0001	0.2291	<0.0001
P/E Multiple (mdfy2)	0.2963	<0.0001	0.1633	<0.0001	0.3901	<0.0001	0.2674	<0.0001
RIVM (2-year / 1.5% terminal value)	-0.0903	<0.0001	-0.1838	<0.0001	0.3381	<0.0001	0.2913	<0.0001
RIVM (2-year / 3% terminal value)	-0.0003	<0.0001	-0.0868	<0.0001	0.3781	<0.0001	0.2648	<0.0001
AEGM (2-year / no terminal value)	-0.2277	<0.0001	-0.2572	<0.0001	0.3311	<0.0001	0.2577	<0.0001

Panel B: Sub-Sample A *(high intangile-intensive industries)*	**Signed Prediction Errors**				**Absolute Prediction Errors**			
	Mean	p-value	Median	p-value	Mean	p-value	Median	p-value
P/E Multiple (mdfy1)	0.0202	0.2892	-0.0685	0.4561	0.4158	<0.0001	0.2846	<0.0001
P/E Multiple (mdfy2)	0.3913	<0.0001	0.2652	<0.0001	0.4947	<0.0001	0.3869	<0.0001
RIVM (2-year / 1.5% terminal value)	-0.1039	<0.0001	-0.2228	<0.0001	0.3905	<0.0001	0.2526	<0.0001
RIVM (2-year / 3% terminal value)	-0.0001	0.0456	-0.0650	0.0919	0.4385	<0.0001	0.3341	<0.0001
AEGM (2-year / no terminal value)	-0.2566	<0.0001	-0.2938	<0.0001	0.3719	<0.0001	0.2948	<0.0001

Panel C: Sub-Sample B *(low intangile-intensive industries)*	**Signed Prediction Errors**				**Absolute Prediction Errors**			
	Mean	p-value	Median	p-value	Mean	p-value	Median	p-value
P/E Multiple (mdfy1)	0.0041	0.9892	0.0057	0.6561	0.2257	<0.0001	0.2610	<0.0001
P/E Multiple (mdfy2)	0.1600	<0.0001	0.1624	0.0001	0.2827	<0.0001	0.2234	<0.0001
RIVM (2-year / 1.5% terminal value)	-0.0794	<0.0001	-0.1535	<0.0001	0.3144	<0.0001	0.2607	<0.0001
RIVM (2-year / 3% terminal value)	-0.0038	0.5621	-0.9364	0.9189	0.3636	<0.0001	0.2502	<0.0001
AEGM (2-year / no terminal value)	-0.1953	<0.0001	-0.2269	<0.0001	0.3453	<0.0001	0.2529	<0.0001

Table 5 reports the results for both parametric (t-test) and non-parametric (Wilcoxon signed rank) tests within the respective samples and for all models. These tests were conducted at a significance level of 5%. Thus, a p-value below 5% indicates a statistically significant lack of valuation accuracy or/and significant biased valuation.

Regarding valuation bias, it is possible to conclude the models' tendency to under- or overvalue. The results stated on table 5 show that P/E (1-year-ahead earnings) for all samples and RIVM (3% continuous growth[9]) for the two sub-samples do not result in a statistically significant mean bias, which means that models do not tend to either under- or overvalue.

When focusing on the stock- versus flow-based valuation models, there is an overall predisposition for flow-based valuation models to undervalue since mean valuation errors result in negative numbers. The tendency for flow-based models to undervalue in the sub-samples is relatively constant with a mean bias of -7.94% to -10.36.% for the RIVM (1.5% continuous growth[10]) and a higher bias for the AEGM of -19.53% to -25.66%. Accordingly, the AEGM shows the highest signed mean valuation errors. Flow-based models result in equally biased value estimates regardless industrial allocation.

Industry differences become apparent when focusing on P/E multiple. Bias is significantly higher for high intangible-intensive industries compared to low intangible-intensive industries, which, in the case of the P/E (mdfy1), is the second smallest bias of the sample. In addition, P/E multiples indicate a slightly overvaluation, which is consistent with Liu *et al.* (2007). According them, multiple valuations result in positive bias, based on industry matching.

Concerning valuation accuracy, all models result in statistically significant mean absolute valuation errors, demonstrating a relevant lack of accuracy. Even though, there are relevant differences when focusing on each model separately.

P/E (1-year-ahead earnings) is the model with the lower accuracy value in the low intangible-intensive industries, with 22.57% of mean valuation accuracy followed by P/E multiple (2-year-ahead earnings) with 28.27% . Sub-sample A, on the contrary, has flow-based valuation models giving the lowest mean absolute valuation by missing, on average, 37.19% and 39.05% of price at valuation date, respectively for AEGM and RIV (1.5%). Comparing the two RIV models, the model with an inferior continuous growth (1.5%) outperforms its 3% alternative.

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[9] For the sake of simplicity, from now on, stated as 3%

[10] For the sake of simplicity, from now on, stated as 1.5%

Sub-sample A does not reveal similar results vis-à-vis sub-sample B, while P/E multiple reveals to be the superior model for sample B, AEGM is the outperformer model for sub-sample A. For the low intangible-intensive industry the 1-year-ahead P/E shows the least lack of accuracy, demonstrating that valuation performance, in this sub-sample, increases with the extension of the forecast horizon (Liu *et. al* (2002, 2007) and Lie and Lie (2002)). The AEGM is, again, the best flow-based model in terms of absolute valuation errors for high intangible-intensive firms. This fact can be explained by the increasing complexity of valuing intangible-intensive firms, which demands for more complex and comprehensive valuation models (Koller *et al*., 2005).

The larger valuation errors indicated by high intangible-intensive industries can be justified by higher volatility, instability and uncertain future expectation concerning these industries. According to Gu and Wang (2005), the superior information complexity of intangible assets increases the difficulty to assimilate information, which, consequently, raises forecast error for sub-sample A.

In conclusion, stock-based valuation models show the best results for both accuracy and bias valuation errors when analyzing low intangible-intensive industries. On the other hand, high intangible-intensive industries result in a better performance when flow-based valuation models are applied.

3.4.2.2 Cross-Sample Analysis of Valuation Errors

This section associates both sub-samples (A and B) to understand whether (or not) valuation models differ in bias and accuracy. Both parametric (two sample t-test) and non-parametric (Wilcoxon rank sum test) tests are conducted.

The hypotheses applied for the samples in the two sample t-test are the following:

H_0 : Mean valuation $\text{error}_{high\ intangible} =$ Mean valuation $\text{error}_{low\ intangible}$

H_1 : Mean valuation $\text{error}_{high\ intangible} \neq$ Mean valuation $\text{error}_{low\ intangible}$

Regarding the Wilcoxon rank sum test, the hypotheses tests used are stated below:

H_0 : Median valuation $\text{error}_{high\ intangible} =$ Median valuation $\text{error}_{low\ intangible}$

H_1 : Median valuation $\text{error}_{high\ intangible} \neq$ Median valuation $\text{error}_{low\ intangible}$

Table 6 - Cross-sample analysis of valuation errors

Signed Prediction Errors	Mean Valuation Errors Sub-Sample A (high intangible-intensive industries)	Mean Valuation Errors Sub-Sample B (low intangible-intensive industries)	p-value	Median Valuation Errors Sub-Sample A (high intangible-intensive industries)	Median Valuation Errors Sub-Sample B (low intangible-intensive industries)	p-value
P/E Multiple (mdfy1)	0.0202	0.0041	<0.0001	-0.0685	0.0057	<0.0001
P/E Multiple (mdfy2)	0.3913	0.1600	<0.0001	0.2652	0.1624	<0.0001
RIVM (2-year / 1.5% terminal value)	-0.1039	-0.0794	<0.0001	-0.2228	-0.1535	0.9732
RIVM (2-year / 3% terminal value)	-0.0001	-0.0038	0.2125	-0.0650	-0.9364	0.2861
AEGM (2-year / no terminal value)	-0.2566	-0.1953	<0.0001	-0.2938	-0.2269	<0.0001
Absolute Prediction Errors	**Mean Valuation Errors Sub-Sample A** (high intangible-intensive industries)	**Mean Valuation Errors Sub-Sample B** (low intangible-intensive industries)	p-value	**Median Valuation Errors Sub-Sample A** (high intangible-intensive industries)	**Median Valuation Errors Sub-Sample B** (low intangible-intensive industries)	p-value
P/E Multiple (mdfy1)	0.4158	0.2257	<0.0001	0.2846	0.2610	<0.0001
P/E Multiple (mdfy2)	0.4947	0.2827	<0.0001	0.3869	0.2234	<0.0001
RIVM (2-year / 1.5% terminal value)	0.3905	0.3144	<0.0001	0.2526	0.2607	<0.0001
RIVM (2-year / 3% terminal value)	0.4385	0.3636	<0.0001	0.3341	0.2502	<0.0001
AEGM (2-year / no terminal value)	0.3719	0.3453	<0.0001	0.2948	0.2529	<0.0001

Table 6 reports the test results for the equality of mean (two sample t-test) and median (Wilcoxon rank sum test) across the respective samples and for all models. These tests were conducted at a significance level of 5%.

Focusing on signed valuation errors, except for the RIVM (3%), results suggest divergent mean signed valuation errors across sub-samples. Regarding median valuation errors, most part of the models show statistically different errors for the sub-samples, excluding the RIVM. Thus, both industries reveal to have different bias between each other.

Observing valuation accuracy, all models, on average, provide also for statistically different mean valuation errors across the sub-samples.

3.4.2.3 Difference in Valuation Errors Between Valuation Models

The following section intends to compare valuation models performance based on models' characteristics as stock- or flow-based valuation models.

Mean and median differences in valuation errors (at a 5% significance level) are described in table 8. The hypotheses used to perform the parametric and the non-parametric tests are stated below.

The hypotheses applied for all samples in the paired sample t-test are the following:

H_0 : Mean valuation $\text{error}_{high/low\ intangible} = 0$

H_1 : Mean valuation $\text{error}_{high/low\ intangible} \neq 0$

Regarding the Wilcoxon signed rank test, the hypotheses tests used are below:

H_0 : Median valuation $\text{error}_{high/low\ intangible} = 0$

H_1 : Median valuation $\text{error}_{high/low\ intangible} \neq 0$

Table 7 - Models valuation performance

Panel A: Pooled Sample	**Mean**	**p-value**	**Median**	**p-value**
P/E (mdfy1) vs. P/E (mdfy2)	-0.0702	<0.0001	-0.0679	<0.0001
RIVM (2-year + 1.5% TV) vs. RIVM (2-year / 3% TV)	0.0461	<0.0001	-0.0196	<0.0001
RIVM (2-year + 1.5% TV) vs. AEGM (2-year / no terminal value)	0.0039	0.4581	-0.0339	<0.0001
RIVM (2-year + 3% TV) vs. AEGM (2-year / no terminal value)	0.0411	<0.0001	-0.0454	<0.0001
P/E (mdfy1) vs. RIVM (2-year / 1.5% TV)	-0.0241	0.0011	-0.0294	<0.0001
P/E (mdfy1) vs. RIVM (2-year / 3% TV)	-0.0641	<0.0001	0.3785	<0.0001
P/E (mdfy1) vs. AEGM (2-year / no terminal value)	-0.0213	0.0031	-0.0501	<0.0001

Panel B: Sub-Sample A *(high intangile-intensive industries)*	**Mean**	**p-value**	**Median**	**p-value**
P/E (mdfy1) vs. P/E (mdfy2)	-0.1423	<0.0001	-0.0974	<0.0001
RIVM (2-year + 1.5% TV) vs. RIVM (2-year / 3% TV)	0.0659	<0.0001	-0.0188	0.2201
RIVM (2-year + 1.5% TV) vs. AEGM (2-year / no terminal value)	0.0099	0.0197	-0.0371	<0.0001
RIVM (2-year + 3% TV) vs. AEGM (2-year / no terminal value)	0.0722	<0.0001	-0.0469	<0.0001
P/E (mdfy1) vs. RIVM (2-year / 1.5% TV)	0.0374	0.0131	-0.0034	0.6749
P/E (mdfy1) vs. RIVM (2-year / 3% TV)	-0.0458	0.0091	-0.0110	0.3276
P/E (mdfy1) vs. AEGM (2-year / no terminal value)	0.0366	0.0003	-0.0253	0.0298

Panel C: Sub-Sample B *(low intangile-intensive industries)*	**Mean**	**p-value**	**Median**	**p-value**
P/E (mdfy1) vs. P/E (mdfy2)	0.0300	0.0005	-0.0189	<0.0001
RIVM (2-year + 1.5% TV) vs. RIVM (2-year / 3% TV)	0.0216	<0.0001	-0.0241	<0.0001
RIVM (2-year + 1.5% TV) vs. AEGM (2-year / no terminal value)	-0.0025	0.3251	-0.0290	<0.0001
RIVM (2-year + 3% TV) vs. AEGM (2-year / no terminal value)	0.0118	0.0345	-0.0568	<0.0001
P/E (mdfy1) vs. RIVM (2-year / 1.5% TV)	-0.0594	<0.0001	-0.0370	<0.0001
P/E (mdfy1) vs. RIVM (2-year / 3% TV)	-0.0738	<0.0001	-0.0354	<0.0001
P/E (mdfy1) vs. AEGM (2-year / no terminal value)	-0.0580	<0.0001	-0.0847	<0.0001

Table 7 reports the test results for the equality of mean (paired sample t-test) and median (Wilcoxon signed rank test) differences in value estimates across samples. Both parametric and non-parametric tests are conducted at a significance level of 5%. MDFY1/2 represent the one and two year ahead forecasted earnings respectively. TV is the abbreviation for terminal value.

The totality of samples, pooled sample and each sub-sample, show, on average, statistical significant mean differences in valuation errors when making a comparison across models. The RIVM (1.5%) and the AEGM seem to be the most closely related, for the pooled sample and sub-sample B, yielding similar value estimates.

When comparing flow-based models versus stock-based models, it is possible to conclude that models, for almost the entire set of samples, have statistical significant mean differences in valuation errors and, accordingly, different value estimates.

3.4.2.4 Explanatory Power of Accounting-Based Valuation Models

OLS regression results are presented next, aiming to explore the explanatory power of the stock- and flow-based valuation models for each sample. The regression model uses share prices as the dependent variable and value estimates of the models are employed as the independent variable. This regression analysis enables to conclude which model performs best in explaining current share prices of both high and low intangible-intensive industries.

The adjusted R^2 for each sample and model is presented in table 9 and represents the fraction of price at valuation date explained via the value estimate.

Table 8 - Explanatory power of valuation models

Panel A: Pooled Sample	**Slope**	**p-value**	**adjusted R^2**
P/E Multiple (mdfy1)	0.7463	<0.0001	0.7461
P/E Multiple (mdfy2)	0.6521	<0.0001	0.7159
RIVM (2-year / 1.5% terminal value)	0.8844	<0.0001	0.6974
RIVM (2-year / 3% terminal value)	0.7366	<0.0001	0.6601
AEGM (2-year / no terminal value)	0.9966	<0.0001	0.7016

Panel B: Sub-Sample A *(high intangile-intensive industries)*	**Slope**	**p-value**	**adjusted R^2**
P/E Multiple (mdfy1)	0.6739	<0.0001	0.7255
P/E Multiple (mdfy2)	0.6083	<0.0001	0.6992
RIVM (2-year / 1.5% terminal value)	0.8690	<0.0001	0.7384
RIVM (2-year / 3% terminal value)	0.7480	<0.0001	0.7174
AEGM (2-year / no terminal value)	0.9896	<0.0001	0.7492

Panel C: Sub-Sample B *(low intangile-intensive industries)*	**Slope**	**p-value**	**adjusted R^2**
P/E Multiple (mdfy1)	0.7842	<0.0001	0.7620
P/E Multiple (mdfy2)	0.7323	<0.0001	0.7774
RIVM (2-year / 1.5% terminal value)	0.8402	<0.0001	0.6225
RIVM (2-year / 3% terminal value)	0.6532	<0.0001	0.5921
AEGM (2-year / no terminal value)	0.9507	<0.0001	0.6572

Table 8 reports the results of estimating the following regression $P_{j,F} = \lambda 0 + \lambda_1 VF_j + \varepsilon_j$ where $P_{j,F}$ 0 observed share price of high intangible-intensive industries (Panel A) and low intangible-intensive industries (Panel B). VF_j = value for security j for the respective models of the panels.

For the pooled sample, table 8 shows that P/E (1 and 2 year-ahead earnings forecast) outperforms the remaining three models (RIVM and AEGM) for a sizeable percentage difference. However, the change between P/E and the AEGM is c.4% with the former indicating a higher explanatory power than the latter.

Firms within the high and low intangible-intensive industries reveal different adjusted R^2 to the pooled sample regarding their percentage values and ranking performance across models. AEGM explains a larger proportion of price at valuation date for sub-sample A, followed by RIVM (1.5%). Thus, consistent with valuation errors on section 3.4.2.1, flow-based models reveal a superior explainability of price values than stock-based models for sub-sample A. On the contrary, sub-sample B shows higher R^2 for stock-based models, both P/E (mdfy1 and mdfy2). AEGM is the outperformer model within flow-based models.

Comparing both P/E multiples (mdfy1 vis-à-vis mdfy2), for both pooled sample and sub-sample A final results for P/E (mdfy2) are weaker compared to P/E (mdfy1). Nevertheless, for low intangible-intensive industries the finding is opposite to the pooled sample and sub-sample A, the extension of the forecast horizon improves valuation performance (Liu et. al (2002, 2007)).

Focusing on the regression values for the sum of samples, high intangible-intensive industries reveal the lowest R^2. However, on a general level, valuation models present, as a whole, explanatory powers superior than 50%, with the pooled sample and the low intangible-intensive industries delivering a higher sound performance. The performance of sub-sample B is better since accounting numbers apparently capture more information for firms with lower unrecorded intangible assets.

3.5 Concluding Remarks on Empirical Results

A considerable number of author such as Lev (2001), stated that accounting measures of performance are expected to be less relevant for intangibles-rich firms, pointing out that accounting is stronger in valuing tangible assets and weaker in valuing intangible assets.

As revealed by the empirical results, stock-based valuation models indicate a superior and solid valuation performance vis-à-vis flow-based valuation models, for the low intangible-intensive industries, which is consistent with the findings of Liu *et. al* (2001, 2007). Even though, for high intangible-intensive industries there is a superiority of flow-based models (Frankel and Lee, 1998; Lee and Swaminathan, 1999). These results are consistent with Trueman et al. (2002) and Imam *et. al* (2008). According to their studied, more complex valuation techniques result in better performance values, particularly in industries where accounting measurement it not able to properly estimate firm value.

In addition, AEGM demonstrates a sound performance, revealing to be the best flow-based valuation model. Particularly, AEGM continuously outperformed the RIVM, linking the results to the literature presented by Ohlson (2005) and Ohlson and Juettner-Nauroth (2005).

The entire empirical analysis reveals a solid performance of multiple-based valuation models, all values equal or superior to 70%. Thus, stock-based models can be perceived as a viable valuation model for both industries.

Chapter 4

Small Sample Analysis

4.1 Hypothesis and Main Literature

According to Hall (2001) the valuation effect of intangible assets on firms' market value is necessary to be studied. With a fundamental role in the value creation process, Wyatt (2005) underlines the need for investors to access even more information about the intangibles of the firms. Analysts' reports are considered one reliable source to minimize information asymmetry.

For Lev and Zarowin (1999), the increasing importance of intangibles threatens the usefulness of published financial statements. Nevertheless, critics claim that investors are exposed to satisfactory information beyond the financial reports.

The small sample analysis aims to analyse analysts' reports and understand, for instance, whether valuation models, which academics regard as being the most accurate, are the same models used by practitioners. A model showing a superior performance in valuing firms in high versus low intangible-intensive industries in the theoretical setting does not necessarily need to be the dominant valuation model applied by practitioners.

Subsequently, following the first analysis, an evaluation of analysts' recommendations is compared across each industry sub-sample. In addition, forecasting behaviour is examined between each industry group. Forecast horizons used by analysts in the reports are examined across the two sub-sets of firms in order to evaluate the choice between longer and shorter forecasted number of years. Ramnath *et al.* (2008) argues that the persistence of biases in analysts' forecasts is still an open question. However, these biases are likely to include optimism at longer horizons and pessimism at shorter horizons.

Finally, a complementing analysis focusing on firms' characteristics, such as market size and volatility, is considered. In addition, a focus on firms' analysts' coverage is subject to study.

4.2 Data and Sample selection

The small sample analysis is based on analysts' reports from the Thomson Research database. All the sample reports correspond to publicly firms trading in the London Stock Exchange Market (principal and secondary). This section considers only reports with at least five pages length (the media of the analysed reports is 14 pages per report), so as to exclude report updates and summaries of analysts' conference calls. Extremely short reports do not contain the relevant information and often focus on the implications of a particular event or update of previous earnings' forecast without mentioning or explaining the rationale and main valuation model employed. In addition, in order to obtain the maximum possible consistency between the two samples, firms in each sub-sample are characterised by different market sizes and multiple investment houses Accordingly, the number of investment houses included in the final sample are different across sectors so as to reflect genuine differences and unbiased results.

Table 9 - Firms belonging to high and low intangible-intensive industries

High-intensive Intangible Industries		**Low-intensive Intangible Industries**	
3-digit SIC	Companies	3-digit SIC	Companies
	Glaxo Smith Kline		African Minerals
283	Hikma Pharmaceuticals	101	Anglo American
	Shire		Ferrexpo
	Domino Printing Sciences		Bumi
357	Imagination Technologies Group	122	Hargreaves Services
	Xaar		New World Resources
	ARM Holdings		Cairn Energy
367	CSR	131	Genel Energy
	Dialight		Enquest
	British Sky Broadcasting		Barratt Developments
483	ITV	152	Berkeley Group
	Perform Group		Great Portland Estates
	Fidessa Group		Keller
737	Micro Focus International	353	Melrose
	Sage Group		Somero

Industry classification for the two samples is based in the SIC codes of Collins *et. al* (2007) and on the criteria already applied for the large sample analysis (section 3.3).

The analysis considers reports, in a total of 30,belonging to two different industries (each industry with 15 companies) aiming to (1) identify the main and primary valuation model applied by each firm in the sample. So as to have consistency among results and a meaningful comparison across both analysis – large and small - the separation of the industries among high and low intangible-intensive, was based on the same criteria related before on section 3.3. Based on Collins *et al.* (1997) and the 3-digit SIC codes, identified for intangible-intensive industries, firms are selected. The remaining industry groups create the low intangible-intensive sample and the possible 15 firms to choose from. In order to increase the chances to obtain suitable and relevant results, the low intangible-intensive sub-sample focused on industries particularly recognized as being low intangible industries. The final sample is presented in table 9.

4.3 Research Design

The research design section is in conformity with the analysis followed by Demirakos *et al.* (2004). In order to classify a valuation model as the dominant valuation model, it needs to be the model most closely associated or directly referred to in the justification of the analysts' target price. When a report uses only one model, it is scored as the main valuation model. However, if analysts apply more than one model, first, the valuation section of the report is checked to see which model is highlighted. Besides, the first page of the report, where the main model is normally presented, is examined. Even though, sometimes, there can be the case where no assessment yields a clear and specific model. As suggested by Demirakos *et al.* (2004), in this example, the differences between analysts' alternative value estimates and the analysts' final target price are calculated, the dominant model is the one closest to the target price.

Following the first analysis, a qualitative examination is applied aiming to focus on how forecasts and investment ratings are presented. Finally, market size, volatility and analyst coverage are the three key variables under consideration with the objective of finding a possible relation between these variables and firms' industry characteristics.

4.3.1 Primary valuation models

Regarding the dominant valuation model employed by analysts, the objective is mainly to evaluate which model is usually applied for the high and the low-intangible intensive industries and conclude whether final results are different form each sample and if they are consistent with the empirical results achieved in the large sample analysis (section 3.3).

Table 10 – Valuation models employed by analysts in the two samples

		Stock-based Valuation Models Single Period					Flow-based Valuation Models Multiperiod		
High Intangible-intensive Industries	# Reports	Earnings	Sales	NAV	Assets	CF	DCFM	RIVM	Other (specific)
SIC 283	3	3	0	0	0	0	1	0	0
%		*75.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*25.00%*	*0.00%*	*0.00%*
SIC 357	3	3	1	0	0	0	0	0	0
%		*75.00%*	*25.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*
SIC 367	3	1	1	0	0	0	1	0	0
%		*33.33%*	*33.33%*	*0.00%*	*0.00%*	*0.00%*	*33.33%*	*0.00%*	*0.00%*
SIC 483	3	2	0	0	0	0	2	0	0
%		*50.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*50.00%*	*0.00%*	*0.00%*
SIC 737	3	2	0	0	0	0	1	0	0
%		*66.67%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*33.33%*	*0.00%*	*0.00%*
Final Distribution				72.22%				27.78%	
Low Intangible-intensive Industries	# Reports	Earnings	Sales	NAV	Assets	CF	DCFM	RIVM	Other (specific)
SIC 101	3	1	0	2	0	0	2	0	0
%		*20.00%*	*0.00%*	*40.00%*	*0.00%*	*0.00%*	*40.00%*	*0.00%*	*0.00%*
SIC 122	3	2	0	0	0	0	2	0	0
%		*50.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*50.00%*	*0.00%*	*0.00%*
SIC 131	3	0	0	2	0	0	1	0	0
%		*0.00%*	*0.00%*	*66.67%*	*0.00%*	*0.00%*	*33.33%*	*0.00%*	*0.00%*
SIC 152	3	2	0	1	0	0	1	0	0
%		*50.00%*	*0.00%*	*25.00%*	*0.00%*	*0.00%*	*25.00%*	*0.00%*	*0.00%*
SIC 353	3	2	0	1	0	0	0	0	0
%		*66.67%*	*0.00%*	*33.33%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*
Final Distribution				68.42%				26.32%	

Table 10 presents the distribution of the main valuation models according to analysts' reports from each company for both samples (high versus low intangible-intensive industries).

According to table 10, financial analysts prefer stock-based valuation models as the dominant model to value companies, whether they belong to high or low intangible-intensive industries. In fact, across both samples, results are similar, with 72.22% of stock-based valuation models vis-à-vis 68.42% of flow-based valuation models.

Regarding these former models, high intangible-intensive industries present a 27.78% of flow-based valuation models vis-à-vis 26.32% for low intangible-intensive industries. In this case, the superiority of the stock-based valuation models as the most used valuation models by analysts is clear. Nevertheless, when focusing on each of the two models' classification, a deeper analysis can be made.

To value high intangible-intensive industry firms, analysts primarily adopt an earnings-based multiple valuation, since 11 out of 15 reports employ an earnings multiple as justification for their target price while 2 reports employ a sales-based multiple valuation, particularly, the EBITDA/SALES multiple. DCFM model is the dominant model in 5 reports out of a total of 15. In the case of low intangible-intensive industry firms, 7 out of the 15 reports are earnings-based multiple valuation models where as 6 out of 15 reports are both NAV and DCF models. The main distinction for the two samples is the use of the NAV model for low intangible-intensive firms, 6 companies versus 0 for the high intangible-intensive industry sample.

This difference can be justified by key industry characteristics belonging to the low intangible sample. Oil and Gas E&P companies are present in the final sample of the low intangible-intensive industries sample. Analysts commonly value these types of firms by the NAV methodology. The NAV model is characterized by not assuming a perpetual growth. Instead, it assumes that companies add nothing to its reserves and produce 100% of their reserves until their runs out of natural resources completely (Carmichael *et al.,* 2007). Investment houses apply different models according to certain companies' characteristics and, in this sample (mainly in SIC 101 and 132), NAV continues to be the primary valuation yardstick for pure E&P companies (JP Morgan).

Although table 11 shows a slight shift towards stock-based valuation models in high intangible-intensive industries, the difference is not relevant to presume a usual tendency to these firms to be valued by stock-based valuation models. Nevertheless, it seems evident the use of earnings-based multiples when valuing intangible-intensive firms. Analysts probably feel a need to use comparative valuation techniques as a starting point even if they are not their preferred valuation choice. (Demirakos *et al*., 2004)

Results are consistent with sub-sample B of the large sample analysis but not with sub-sample A. The small sample results reveal a theoretical superiority of single valuation models, namely stock-based models (P/E), versus flow-based models. However, according to academia, firms with high levels of intangibles are properly valued by flow-based valuation models (Trueman et al. (2002), Sougiannis et al. (2000) and Imam *et al.* (2008)). Theoretical superiority not reveals to be equivalent to analysts' preferred valuation model. Evidence of Demirakos *et al.* (2004) suggests that a simple multiples-based approach, where multiples are derived from data for comparable firms, is favoured by valuation practitioners. This approach is likely to be attractive because of its relative simplicity.

4.3.2 Analysts' recommendations

On this section, as mentioned before, the purpose is to evaluate whether final recommendations of analysts differ from industry groups. The hypothesis examined are presented below:

$$H_3 : \#\, positive\ ratings_{\ high\ intangible} = \#\, positive\ ratings_{\ low\ intangible}$$

$$H_3 : \#\, positive\ ratings_{\ high\ intangible} \neq \#\, positive\ ratings_{\ low\ intangible}$$

Table 11 – Analysts' ratings for high and low intangible-intensive industries

	Ratings		
High Intangible-intensive Industries	Buy	Hold	Sell
SIC 283	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
SIC 357	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
SIC 367	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
SIC 483	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
SIC 737	2	0	1
%	*66.67%*	*0.00%*	*33.33%*
Total	10	4	1
%	*66.67%*	*26.67%*	*6.67%*
Low Intangible-intensive Industries	Buy	Hold	Sell
SIC 101	3	0	0
%	*100.00%*	*0.00%*	*0.00%*
SIC 122	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
SIC 131	3	0	0
%	*100.00%*	*0.00%*	*0.00%*
SIC 152	3	0	0
%	*100.00%*	*0.00%*	*0.00%*
SIC 353	2	1	0
%	*66.67%*	*33.33%*	*0.00%*
Total	13	2	0
%	*86.67%*	*13.33%*	*0.00%*
P-value T-test		0.6999	

Table 11 summaries the distribution of analysts' investment ratings based on the valuation models examined on section 4.3.1. The p-value indicates the t-test of the equality of ratings between the samples at a significance level of 5%.

Table 11 presents three types of recommendation –"buy", "hold" and "sell", each meaning a positive, neutral and negative valuation, respectively. In this analysis, and in order to answer the statistical hypotheses stated before, positive ratings are assumed to be both "buy" and "hold" recommendations. Results from table 11 show a higher percentage of positive ratings, 86.67%, for low intangible-intensive industries in comparison to high intangible-intensive industries, 66.67%. In respect to neutral valuations, considered as a positive recommendation as well, sub-sample A reveals a superior number of neutral recommendations (26.67% vs 13.33%) and also the only negative valuation of all the 30 reports. The negative rating is for Micro Focus International. For this company, analysts ground their judgment on the structural problems with the business, declining end-markets, material earnings risk and, lastly, to the increasingly persistent maintenance attrition (Jefferies, 2011).

The findings on this section are consistent with previous literature indicating a tendency for analysts' recommendations to be biased toward a buy (Demirakos *et al.* 2004).

The neutral valuations of high intangible-intensive industries correspond to GlaxoSmithKline, Domino Printing Sciences, CSR and British Sky Broadcasting Group. Challenging years that firms will face regarding specific industry/business characteristics and to macro/economic conditions backs the reason for analysts' ratings. Specifically for CSR, in which DeutsheBank reflects the macro uncertainty and muted revenue growth in the mid-term to justify the neutral valuation.

According to Bradshaw (2002), valuations based on P/E multiples and expected growth are more likely to be used to support favorable recommendations, while qualitative analysis of a firm's fundamentals is more likely to be employed to justify less favorable recommendations.

By analyzing the p-value of table 11 it is possible to conclude that the difference in valuation ratings between the two samples is not statistically significant. The null hypothesis of the total number of positive ratings for the two samples being equal is accepted for a 0.05 significance level.

4.4.3 Forecast horizon in analysts' reports

With the purpose of examining whether forecast horizon length differs across the industries, the following hypotheses are used:

$$H_4: Forecast\ horizon_{\ high-intangible} = Forecast\ horizon_{\ low-intangible}$$

$$H_4: Forecast\ horizon_{\ high-intangible} \neq Forecast\ horizon_{\ low-intangible}$$

Table 12 – Forecast horizons for small sample firms

	Forecast Horizon				
High Intangible-intensive Industries	2	3	4	5	> 5
SIC 283	0	1	0	1	1
%	*0.00%*	*33.33%*	*0.00%*	*33.33%*	*33.33%*
SIC 357	1	1	1	0	0
%	*33.33%*	*33.33%*	*33.33%*	*0.00%*	*0.00%*
SIC 367	1	1	0	1	0
%	*33.33%*	*33.33%*	*0.00%*	*33.33%*	*0.00%*
SIC 483	0	1	1	0	1
%	*0.00%*	*33.33%*	*33.33%*	*0.00%*	*33.33%*
SIC 737	0	3	0	0	0
%	*0.00%*	*100.00%*	*0.00%*	*0.00%*	*0.00%*
Total	2	7	2	2	2
%	*13.33%*	*46.67%*	*13.33%*	*13.33%*	*13.33%*
Low Intangible-intensive Industries	2	3	4	5	>5
SIC 101	3	0	0	0	0
%	*100.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*
SIC 122	1	2	0	0	0
%	*33.33%*	*66.67%*	*0.00%*	*0.00%*	*0.00%*
SIC 131	1	2	0	0	0
%	*33.33%*	*66.67%*	*0.00%*	*0.00%*	*0.00%*
SIC 152	0	2	0	1	0
%	*0.00%*	*66.67%*	*0.00%*	*33.33%*	*0.00%*
SIC 353	0	3	0	0	0
%	*0.00%*	*100.00%*	*0.00%*	*0.00%*	*0.00%*
Total	5	9	0	1	0
%	*33.33%*	*60.00%*	*0.00%*	*6.67%*	*0.00%*
P-value T-test			0.0252		

Table 12 outlines the distribution of analysts' forecast horizons employed in the reports. The p-value indicates the t-test of the equality of forecast horizons between the samples at a significance level of 5%.

Table 12 presents the distribution of forecasting horizons applied in the reports of both sub-samples. The high intangible-intensive industries sample have 46.67% of the reports featuring accounting forecasts for the next 3 years while the low intangible sample has 60%. A complex analysis of the values enables to understand that firms in the low intangible sample have their forecast horizons equal to 2 and 3 years while the high intangible sample presents a wider distribution, featuring forecast horizons for much more years (13.33% for more than 5 years). Companies in the drugs (SIC 283) industry are, on average, the firms with longer forecast horizons. This fact can be justified by the uncertainty of the industry regarding new products success/failure. Since this industry is characterised by possible long future economic benefits from investments, forecast horizon needs to increase in order to incorporate the possible future cash flows.

The p-value of 0.0252 enables to reject the null hypothesis of forecast horizons being equal for both samples. Hence, it is possible to conclude that the forecast horizon applied for high versus low intangible-intensive industries is significantly different.

4.4.4 Supplement analysis on key firms' characteristics

In order to complement the previous analysis, specific firms' characteristics are going to be analysed. The aim is to evaluate whether the intangible characteristics of the industries (high vs low) is associated with certain specific features of the companies, such as market size, volatility of the firm and, finally, analyst coverage.

4.4.4.1 Market size

The hypotheses considered for this section are presented below:

H_5: $Market\ Size_{high-intangible} = Marlet\ Size_{low-intangible}$

H_5: $Market\ Size_{high-intangible} \neq Market\ Size_{low-intangible}$

Table 13 – Market size of the firms in the small sample analysis

	Market Capitalisation				
High Intangible-intensive Industries	Large	Medium	Small	Micro	Nano
SIC 283	2	0	1	0	0
%	*66.67%*	*0.00%*	*33.33%*	*0.00%*	*0.00%*
SIC 357	0	1	1	1	0
%	*0.00%*	*33.33%*	*33.33%*	*33.33%*	*0.00%*
SIC 367	0	1	2	0	0
%	*0.00%*	*33.33%*	*66.67%*	*0.00%*	*0.00%*
SIC 483	1	1	1	0	0
%	*33.33%*	*33.33%*	*33.33%*	*0.00%*	*0.00%*
SIC 737	0	1	2	0	0
%	*0.00%*	*33.33%*	*66.67%*	*0.00%*	*0.00%*
Total	3	4	7	1	0
%	*20.00%*	*26.67%*	*46.67%*	*6.67%*	*0.00%*
Low Intangible-intensive Industries	Large	Medium	Small	Micro	Nano
SIC 101	1	1	1	0	0
%	*33.33%*	*33.33%*	*33.33%*	*0.00%*	*0.00%*
SIC 122	0	1	1	1	0
%	*0.00%*	*33.33%*	*33.33%*	*33.33%*	*0.00%*
SIC 131	0	1	2	0	0
%	*0.00%*	*33.33%*	*66.67%*	*0.00%*	*0.00%*
SIC 152	0	1	2	0	0
%	*0.00%*	*33.33%*	*66.67%*	*0.00%*	*0.00%*
SIC 353	0	1	1	0	1
%	*0.00%*	*33.33%*	*33.33%*	*0.00%*	*33.33%*
Total	1	5	7	1	1
%	*6.67%*	*33.33%*	*46.67%*	*6.67%*	*6.67%*
P-value T-test			0.3714		

Table 13 outlines the distribution of the market capitalisation of the companies in both samples. The p-value indicates the t-test of the equality of market sizes between the samples at a significance level of 5%.

Table 13 presents five possible classifications of companies according to their market size. Large cap firms need to have a market capitalisation over \$10 billion. Mid-cap range of market capitalisation is \$2 billion–\$10 billion while small market size companies have between \$250 million and \$2 billion in market cap. Finally, the smallest firms, micro and nano, have a market capitalisation below \$250 million and below \$50 million respectively.

The analysis of the table does not permit to extrapolate a complete difference on the industries' results. While the first industry sample has at least 3 large firms (20% of the total), the second industry sample only has 1 large company (6.67% of the total). The p-value of the t-test for the equality of means for the market size of the two samples is higher than 0.05, which means that the null hypothesis is not rejected. Thus, the small difference verified in table 13 between industry samples is not significant and does not demonstrate a tendency for high intangibles firms to be larger than low intangible companies.

4.4.4.2 Volatility – beta (ρ)

In order to analyse a possible tendency between volatility and high versus low intangible-intensive companies, the following hypotheses are tested:

$H_6: Volatility_{\ high-intangible} = Volatility_{\ low-intangible}$

$H_6: Volatility_{\ high-intangible} \neq Volatility_{\ low-intangible}$

Table 14 – Volatility (beta) of the small sample firms

	Beta	
High Intangible-intensive Industries	< 1	> 1
SIC 283	3	0
%	*100.00%*	*0.00%*
SIC 357	0	3
%	*0.00%*	*100.00%*
SIC 367	2	1
%	*66.67%*	*33.33%*
SIC 483	2	1
%	*66.67%*	*33.33%*
SIC 737	3	0
%	*100.00%*	*0.00%*
Total	10	5
%	*66.67%*	*33.33%*
Low Intangible-intensive Industries		
SIC 101	0	3
%	*0.00%*	*100.00%*
SIC 122	1	1
%	*33.33%*	*33.33%*
SIC 131	0	2
%	*0.00%*	*66.67%*
SIC 152	1	2
%	*33.33%*	*66.67%*
SIC 353	1	2
%	*33.33%*	*66.67%*
Total	3	10
%	*20.00%*	*66.67%*
P-value T-test	0.0058	

Table 14 outlines the distribution of the beta value for all companies in the two samples. The p-value indicates the t-test of the equality of market sizes between the samples at a significance level of 5%.

According to table 14 the overall tendency concerning beta and high versus low intangible-intensive industries is straightforward. While high intangible firms present usually a beta lower than 1 (66.67%), low intangible firms have a beta higher than 1 (66.67%). Since the p-value of the t-test for the difference of the beta means is below 0.05, the null hypothesis is rejected and so, the difference between samples mean is statistically significant.

Drugs and iron core industries are the perfect reflection of extremely divergent betas across the industries. While all firms in the drugs industry have a beta below 1, all firms belonging to the iron core industry have a beta higher than 1. According to D'Erasmo and Boedo (2012), firm-level idiosyncratic volatility is negatively correlated with intangible expenditures. Firms that incur in superior intangible expenses are able to serve more markets and diversify market-specific demand risk (D'Erasmo and Boedo,2012). Another explanation for a lower beta in intangible-intensive industries can be related with the fact that intangible industries are often very regulated industries, for example, the biotech/drug and medical equipment industries. Due to increased information transparency of the firm's intangibles a decrease of information complexity is expected to occur. (Barth et al., 2004)

4.4.4.3 Analyst Coverage

To conclude, analyst coverage is analysed between the two samples. The aim is to find a possible existing relation between the number of investment' houses following companies and the intangibles' total asset amount of those firms. For this section, the following hypotheses are considered:

$$H_7: Analyst\ Coverage_{\ high-intangible} = Analyst\ Coverage_{\ low-intangible}$$

$$H_7: Analyst\ Coverage_{\ high-intangible} \neq Analyst\ Coverage_{\ low-intangible}$$

Table 15 – Analyst coverage for the two sample firms in the small sample data

High Intangible-intensive Industries	Analyst Coverage
SIC 283	69
%	*28.51%*
SIC 357	30
%	*12.40%*
SIC 367	58
%	*23.97%*
SIC 483	60
%	*24.79%*
SIC 737	25
%	*10.33%*
Total	242
%	*100.00%*
Low Intangible-intensive Industries	Analyst Coverage
SIC 101	59
%	*27.44%*
SIC 122	35
%	*16.28%*
SIC 131	57
%	*26.51%*
SIC 152	46
%	*21.40%*
SIC 353	18
%	*8.37%*
Total	215
%	*100.00%*
P-value T-test	0.3714

Table 15 reports analysts' coverage for each industry in the two samples. The p-value indicates the t-test of the equality of analyst coverage between sub-sample A and B at a significance level of 5%.

The results presented in table 15 reveal superior analyst coverage for high intangible-intensive firms (242) in comparison to low intangible-intensive companies (215). In addition, the p-value statistic reveals that the difference is statistically significant. First, since analyst coverage is defined as addressing a part of the problem, an important study by Lang and Lundholm (1996) concludes that firms with higher quality of disclosure attract larger number of analysts. Whereas, another study by Barth *et al.* (2001) finds that analysts have a greater incentive to follow firms that have higher investments in intangibles that includes R&D. Both these findings are consistent with results verified in table 15.

Nevertheless, it is necessary to highlight analyst coverage positive dependency on trading volume and frequency of access to capital markets (Barth *et. al*, 2001). Although sample reports diversification in terms of size and volume across the two sub-samples is considered and minimised the best way possible, biased results regarding this analyst coverage are powerfully real. In addition, analysts' decisions to cover firms depend also on private benefits (trading or investment banking fees), and costs. Since these benefits and costs differ across firms, analysts' greater incentives to cover firms with intangible assets may not result in greater coverage for all such firms.

4.5 Concluding remarks

In conclusion, although this analysis is, due to its nature, subject to unreliable results, analysts value both high and low intangible-intensive firms predominantly via stock-based valuation models. This findings are consistent with results from the large sample analysis for low intangible-intensive industries but contrary to high-intangible intensive industries. The overall good performance justifies the general tendency of analysts to generate value estimates via market multiples (Demirakos *et al*., 2004; Fernández, 2002; Guo *et al.* 2005).

Furthermore the analysis points out that analysts significantly extend their forecasting horizon for firms with high level of intangibles. The most likely reason for doing so may be the fact that the analyst tries to present the valued equity in a way that future economic benefits can be incorporated in companies results. In a high intangible industry, these economic benefits, when capitalised, reflect a need to increase forecast horizons in order to incorporate the positive results arriving in the longer future.

The complementing analysis of firms' characteristics underlines the cyclicality of the low intangible-intensive industry firms and also analysts greater incentives to cover firms whose value is less well captured by accounting amounts. This suggests analysts provide information that at least partially compensates for information not provided by the financial accounting system.

Chapter 5
Conclusion

The attempt to verify the empirical findings in the small sample analysis can be regarded as broadly in line with the research of Demirakos *et al.* (2004) Tasker (1998) and Block (1999) arguing for the deviation from empirically superior models by practitioners.

The comparison of valuation errors between industries, and consistent with Barth *et al*. (2005) prediction, show a significantly positive association between analysts' forecast error and the amount of the firm's intangible assets. High information complexity of intangibles may likely increase the difficulty of assimilating intangible information, complicating analysts' task of earnings forecast.

Reports on the two samples display a consistency of empirical results and the applied valuation models.

The extension of forecast horizons in analyst reports gives evidence to the tendency to generate favourable forecasts outlined. It is likely that analysts extend forecast horizons to mask current underperformance in order to present the equity in a favourable light.

The main caveat in this thesis and its analysis is the fact the dubious classification of what high and low intangible-intensive firms are and how can they accurately be classified when trying to capture the value that cannot be measured by the firms' financial statements and accounting reports. In addition, the existent financial market crisis causes high volatility in equity markets, making a market-based valuation meaningless. Since the small sample only examines reports from this period the changes in valuation models by analysts may be exceptional and unique in occurrence.

However, this caveat outlines fields for further research: An extended small sample analysis incorporating other periods of economic contraction and more analyst reports would be able to validate if analysts generally change valuation models dependent on the cycle phase or if the observations made are unique and a result of the financial market crisis. Besides, it would be interesting to examine the extent to which analysts' reports systematically differ across brokerage houses or even to test analyst coverage according to intangible industries.

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V Appendix

Derivation RIV equity perspective:

$$V_t^e = \sum_{t=1}^{\infty} \frac{E_t[DIV_{t+1}]}{(1+k_e)^t}$$

$$V_t^e = \frac{E_t[DIV_{t+1}]}{1+k_e} + \frac{E_t[DIV_{t+2}]}{(1+k_e)^2} + \frac{E_t[DIV_{t+3}]}{(1+k_e)^3} + \dots$$

Definition of residual income:

$$RI_t^e = NI_t - k_e \times BVE_{t-1}$$

Clean surplus relation (CSR):

$$BVE_t - BVE_{t-1} = NI_t - DIV_t$$

Given the two previous definitions, dividend can be written as follows:

From CSR – $DIV_t = NI_t$ – $(BVE_t - BVE_{t-1})$

From RI - $NI_t = RI_t^e + k_e \times BVE_{t-1}$

Thus,

$$DIV_t = [RI_t^e + k_e \times BVE_{t-1}]\text{-}(BVE_t - BVE_{t-1}) = RI_t^e - BVE_t + (1+k_e)\times BVE_{t-1}$$

Substituting the equation into the DDM, the value of equity is:

$$V_t^e = \frac{E_t[RI_{t+1}^e - BVE_{t+1} + (1+k_e) \times BVE_t]}{1+k_e} + \frac{E_t[RI_{t+2}^e - BVE_{t+2} + (1+k_e) \times BVE_{t+1}]}{(1+k_e)^2} + \frac{E_t[RI_{t+3}^e - BVE_{t+3} + (1+k_e) \times BVE_{t+2}]}{(1+k_e)^3}$$

DDM can be re-expressed as:

$$V_t^e = BVE_t + \sum_{\tau=1}^{\infty} \frac{E_t[RI_{t+\tau}^e]}{(1+k_e)^\tau}$$

Derivation RIV entity perspective:

$$V_t^{e+d} = \sum_{t=1}^{\infty} \frac{E_t[FCF_{t+1}]}{(1+WACC)^t}$$

$$V_t^{e+d} = \frac{E_t[FCF_{t+1}]}{1+WACC} + \frac{E_t[FCF_{t+2}]}{(1+WACC)^2} + \frac{E_t[FCF_{t+3}]}{(1+WACC)^3} + \dots$$

Definition of residual income:

$$RI_t^{e+d} = NOPAT_t - WACC_t \times NOA_{t-1}$$

Clean surplus relation (CSR):

$NOA_t - NOA_{t-1} = NOPAT_t - FCF_t$

Given the two previous definitions, FCF can be written as follows:

From CSR – $FCF_t = NOPAT_t - (NOA_t - NOA_{t-1})$

From RI - $NOPAT_t = RI_t^{e+d} + WACC \times NOA_{t-1}$

Thus,

$FCF_t = \left[RI_t^{e+d} + WACC \times NOA_{t-1}\right]$ -$(NOA_t - NOA_{t-1}) = RI_t^{e+d} - NOA_t + (1 + WACC)\times NOA_{t-1}$

Substituting the equation into the DDM, the value of entity is:

$$V_t^e = \frac{E_t\left[RI_{t+1}^{e+d} - NOA_{t+1} + (1+WACC)\times NOA_t\right]}{1+WACC} + \frac{E_t\left[RI_{t+2}^{e+d} - NOA_{t+2} + (1+WACC)\times NOA_{t+1}\right]}{(1+WACC)^2} + \frac{E_t\left[RI_{t+3}^{e+d} - NOA_{t+3} + (1+WACC)\times NOA_{t+2}\right]}{(1+WACC)^3}$$

DDM can be re-expressed as:

$$V_t^{e+d} = NOA_t + \sum_{\tau=1}^{\infty} \frac{E_t\left[RI_{t+\tau}^{e+d}\right]}{(1+WACC)^{\tau}}$$

Derivation AEG:

$$V_t^e = \sum_{t=1}^{\infty} \frac{E_t[DIV_{t+1}]}{(1+k_e)^t}$$

$$V_t^e = \frac{E_t[DIV_{t+1}]}{1+k_e} + \frac{E_t[DIV_{t+2}]}{(1+k_e)^2} + \frac{E_t[DIV_{t+3}]}{(1+k_e)^3}$$

Setting valuation date t=0:

$$V_0^e = \frac{E_0[DIV_1]}{1+k_e} + \frac{E_0[DIV_2]}{(1+k_e)^2} + \frac{E_0[DIV_3]}{(1+k_e)^3} + \dots$$

Since that,

$$\frac{y_T}{(1+k_e)^T} \rightarrow 0 \; as \; T \rightarrow \infty$$

Thus,

$$0 = \cancel{y_0} + \frac{y_1 - \cancel{(1+k_e)}y_0}{\cancel{1+k_e}} + \frac{y_2 - \cancel{(1+k_e)}y_1}{\cancel{(1+k_e)^2}} + \frac{y_3 - \cancel{(1+k_e)}y_2}{\cancel{(1+k_e)^3}} + \dots$$

By rewriting DIV in terms of DIV and y:

$$V_0^e = y_0 + \sum_{\tau=1}^{\infty} \frac{E_0\left[y_t + DIV_t - (1+k_e)y_{t-1}\right]}{(1+k_e)^{\tau}}$$

By defining the capitalized next-period earnings:

$y_t = E_0 \frac{[NI_{t+1}]}{k_e}$, t = 0,1,2,…

Substituting y out:

$$V_0^e = \frac{E_0\,[NI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_0\left[\left(\frac{NI_{t+1}}{k_e}\right) + DIV_t - (1+k_e)(\frac{NI_t}{k_e})\right]}{(1+k_e)^{\tau}}$$

$$= \frac{E_0\,[NI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{1}{k_e}\left\{\frac{E_0\left[NI_{t+1} + k_e\,DIV_t - (1+k_e)NI_t\right]}{(1+k_e)^{\tau}}\right\}$$

$$= V_t^e = \frac{E_t\,[NI_{t+1}]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_t[z_{t+\tau}]}{(1+k_e)^{\tau}} \quad where z_t = \frac{1}{k_e}\left[\Delta NI_{t+1} - k_e\,(NI_t - DIV_t)\right]$$

Derivation RIV VS AEG/OJ:

$$V_0^e = BVE_0 + \sum_{\tau=1}^{\infty} \frac{E_0[RI_t^e]}{(1+k_e)^{\tau}} \Leftrightarrow V_0^e = \frac{E_0\,[NI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_t[z_t]}{(1+k_e)^{\tau}}$$

This can be explained by starting with the final formula for the OJ model and derive it to reach the RIV model.

$$V_0^e = \frac{E_0\,[NI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_t[z_t]}{(1+k_e)^{\tau}}$$

$$= BVE_0 + \frac{E_0\,[RI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_0[\Delta RI_{t+1}]}{k_e(1+k_e)^{\tau}}$$

$$= BVE_0 + \frac{E_0\,[RI_1]}{k_e} + \sum_{\tau=1}^{\infty} \frac{E_0[\Delta RI_{t+1}]}{k_e(1+k_e)^{\tau}}$$

$$= BVE_0 + \sum_{\tau=1}^{\infty} \frac{E_0[RI_t^e]}{(1+k_e)^{\tau}}$$