Equity Valuation Using Accounting Numbers in High and Low Price to Performance Firms

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Abstract

The surge of new industries in the economy has made commonplace a situation where firms are trading at prices greatly superior to their financial performance. In such conditions doubts may arise regarding the use of traditional valuation models to estimate the value of high price to performance firms.

This dissertation has as its main goal to determine if there is a variation in terms of performance by traditional valuation models when applied to high and low price to performance firms. Furthermore, the representation of performance by an accounting number is also studied in order to determine if such classification results in significant differences across firms.

It is found that when price to operating income before depreciation (P/OI) is used to separate firms into high and low P/OI sub-samples more significant differences between sub-samples arise than when price to net income (P/NI) is used. Moreover, valuation models are found to be less biased and more accurate, although explaining price worse, when applied to high P/OI firms. Finally, relevant differences are discovered regarding the use of nonfinancial information to represent firm performance by analysts and firms.

Key Words: Operating Income, Operating Income Before Depreciation (OIBDP), Net Income (NI), P/OI, P/NI, Residual Income Model (RIM), Price-Earnings Multiple (P/E), Valuation Errors

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Chapter 1: Introduction

1.1 Motivation

The growth and expansion of the digital economy has paved the way for firms that are highly valued even though their operating performance may be distant from their market value.

Trueman *et al.* (2000) remembered an analyst whose analysis on Amazon.com could justify any valuation between $1-$200 by changing assumptions at a time the company was trading at $130.

Although more than a decade has passed, the situation persists alongside the premise that Internet stocks are difficult to value (Trueman *et al.*, 2000). This problem is most notable when looking at firms not publicly traded: for instance start-ups going through funding rounds or IPOs (Kim and Ritter, 1999).

Nonetheless, a parallel could be drawn with publicly traded firms to state that traditional valuation models perform worse on firms with high price relative to operating performance (P/OP) than on their counterparts that lie in the low end of this ratio.

It is interesting to study if this is a sound claim, given the current market size of companies such as Yahoo and, more recently, Facebook and Twitter - firms that once were[1] or still are included in this category and questioned[2] on the reasonability of their market prices.

1.2 Defining Operating Performance and a High/Low Price to Operating Performance Firm

Operating or operational performance are expressions used interchangeably throughout this dissertation. They designate key financials that lock-in a firm's yearly business functioning in a figure, summing up the level of success achieved for the period.

To illustrate high P/OP firms Trueman *et al.* (2000) used P/E and Price-to-Revenue. Similarly, in this dissertation operating performance will be represented in the large sample analysis by Operating Income Before Depreciation and in the small sample analysis by Net Income. The use of two

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[1] See, for example, Schonfeld, E., 2000. How Much Are Your Eyeballs Worth. *Fortune*, [online]. Available at: <http://archive.fortune.com/magazines/fortune/fortune_archive/2000/02/21/273860/index.htm> [Accessed 2 August 2014].

[2] See, for example, Berman, K., 2013. Is Twitter Really Worth $10 Billion?. *The Wall Street Journal*, [online]. Available at: <http://online.wsj.com/news/articles/SB10001424127887323384604578328303487784818> [Accessed 2 August 2014].

different proxies will allow for a representation of operating performance firstly as the business proper and secondly as the overall success of the firm.

1.3 Outline

This dissertation will take on the abovementioned premise that traditional valuation models perform worse on high P/OP firms. The goal is to find whether there is enough evidence to validate this assertion as well as which valuation method achieves the best results.

With such purpose in mind, the next chapter will start by reviewing the most relevant literature in accounting-based equity valuation. It will be followed by the description of the procedures undertook in the large sample analysis and the interpretation of the results obtained. Immediately after follows the small sample analysis, which will be similarly structured. Naturally, a conclusion encompassing the results gathered and suggesting possible further research seals this dissertation on the behaviour of equity valuation models applied to high and low P/OP firms.

Chapter 2: Literature Review

2.1 Introduction and Basic Concepts

In order to fluently discuss important concepts in chapters three and four, they should first be reviewed and defined in this chapter. This literature review will examine what academia has studied in the field of equity valuation using accounting numbers and how it relates to the work undertaken throughout this dissertation.

It used to be that accounting practices were judged on how well they conformed to certain theoretical models, since it was believed that accounting numbers lacked substantive meaning and consequently had no further use (Ball and Brown, 1968). Nonetheless, Ball and Brown (1968) proved otherwise. Their paper found that a firm's yearly income figure contained 50% or more of all available yearly information.

Thanks to this shift in paradigm, accounting numbers and practices today are regarded as important elements in the process of portraying the value of a business, providing insight into a firm's financial and operational situation as well as its future prospects. Since then, policy-oriented research like the one undertaken in the 1960s has become rare (Lev 1989) and, according to Lee (1999), it was during the 1990s that accounting numbers began being studied for the purpose of estimating shareholder value.

The role of accounting information today can then be described as facilitator of information to be used in valuation and not as a direct measure of the value of a firm (Lee, 1999). Equity valuation itself is essentially an estimate of the present value of expected payoffs to shareholders (Lee, 1999). Thus, it puts a target price on a firm's stock in order to indicate what it is worth; i.e. what is the present value of expected future cash-flows to shareholders. As any other estimate, valuation is at its core subjective and inaccurate and, as such, valuation models are compared not in terms of perfection, but in impreciseness.

Besides providing a figure related to current year earnings, accounting information also helps in forecasting future earnings. For instance, Beaver (1968) determined an earnings report had information if it led to a change in investors' expectations regarding future returns, reflected in market price movement. Looking at key fundamentals alongside important remarks can shed light on otherwise uncertain impending cash-flows thus leading to an alteration in investors' expectations.

Thus, accounting information is, as Ball and Brown (1968) would put it, indeed "useful" for equity valuation. It provides figures for the current financial success of the firm, it contains information to predict its future, and establishes a language allowing information to be passed on and compared across time and firms.

A second key concept is the dichotomy equity (*1*) vs. entity (*2*) perspective. They can also be respectively referred to as the proprietary or shareholders' view and enterprise view. The former concerns the stake belonging to the company's owners, the shareholders, separating it from what is owed to second parties. Valuation under the equity perspective estimates directly what the firm's equity is worth. This is the value most investors and analysts desire to know since it allows them to compare with the valued firm and other companies' current market price and act on the difference.

$$Equity = Assets - Liabilities \tag{1}$$

Conversely, the entity perspective values the firm as its total assets, including both the shareholders' and the firms' creditors' claims. Similarly, cash-flows to owners include not only dividends but all free cash-flow (FCF) net of tax. Thus, when a firm is valued, what is estimated under the equity perspective is the present value of the stream of future dividends, whereas with the entity perspective it is calculated the present value of expected FCF. Furthermore, while in the equity perspective cost of capital meant the cost of equity capital (r_e), under the entity perspective it is represented by the weighted average cost of capital (r_{WACC}).

$$Entity = Assets = Equity\ Claims + Creditor\ Claims \tag{2}$$

2.2 Accounting-Based Valuation Models

Accounting-based valuation models can be broke down into two categories: flows-based models and multiples-based models.

2.2.1 Multiples-Based Models

Multiples-based models are easier to understand (Lie and Lie, 2002). They do not require multi-period forecasts of several parameters; instead they are trusted to include all of these elements in one figure because they rely on comparable firms to mirror the target firm in terms of future cash-flows and exposure to risk. Moreover, they can be used on private firms, which is most useful when valuing IPOs (Alford, 1992) or for M&A activities (Bhojraj and Lee, 2002).

These models estimate the value of a firm by multiplying a value driver by a multiple acquired from a ratio or an average of the ratios of comparable firms' stock price to the value driver (Liu *et al.*, 2002) (*3*). The value driver is the link of multiples-based models to flows-based models, since it is usually a key fundamental that can be traced back to accounting-based flows.

$$Value\ of\ Firm\ i = Value\ Driver_i \times Benchmark\ Multiple \tag{3}$$

Additionally, it should also be remembered that multiples-based valuation can include an intercept. However, Liu *et al.* (2002) consider that the complexities may exceed the benefits of this practice since the improvement in performance is only significant for poor-performing multiples.

The first stage of multiples-based valuation is selecting the value driver. One of the key assumptions is that the value driver is proportional to value. It can be used to reflect the equity or entity perspective: for example net income or net operating profit after tax (NOPAT), respectively.

After that, comparable firms are selected. It is assumed that future cash-flows of comparable firms are similar to the target firm's and that the similarity is extended to risk profiles of comparable and target firms.

Having chosen the set of comparables, it is time to compute the benchmark multiple. The final step consists on applying the benchmark multiple to estimate the value of the target firm (*3*).

2.2.1.1 Selecting the Value Driver

The first important point to bring up is that more than one multiple can be chosen (*4*).

$$Value\ of\ Firm\ i = Weight_1 \times VD_{1,i} \times BM_1 + Weight_2 \times VD_{2,i} \times BM_2 \quad (4)$$

Where $Weight_{1,2}$ are weights assigned to each value driver, designated by $VD_{1,2}$, and $BM_{1,2}$ are the benchmark multiples of each value driver.

The most important criterion in selecting a value driver should be a close correlation with the target firm's value. This implies that the chosen value driver should clearly reflect the firm's performance.

According to Liu *et al.* (2002), forward earnings explain stock prices the best, being that for half of the sample pricing errors were within 15%. Additionally, performance improved as the forecast horizon lengthened (Liu *et al.*, 2002). Historical earnings followed ahead of both cash-flow measures and book value of equity and trumped also sales, the worst performing value driver (Liu *et al.*, 2002). It should be noted, however, that earnings are subject to managerial opportunism and that transitory items, unrelated to intrinsic firm characteristics, can negatively influence the accuracy of the value estimate (Liu *et al.*, 2007).

2.2.1.2 Selecting Comparable Firms

The selection of comparable firms is an important topic not only in multiples-based valuation, but also in academic research for isolating variables and in fundamental analysis and forecast of sales growth ratios or profit margins (Bhojraj and Lee, 2002).

Extrapolating what Alford (1992) wrote on P/E multiples to the general case of multiples-based valuation, the choice of comparables should ideally be made according to variables that explain cross-sectional differences in multiples so that the multiples of comparable firms will be similar to the unknown multiple of the target firm.

In order to achieve this, a single comparable can be chosen or a set of firms based on specific criteria can be selected. In the first scenario the advantage would be that finding a comparable with similarities in key fundamentals might be easier, but on the other hand the impact of its differences, however small, would be heightened in comparison to a benchmark multiple calculated from a set of comparable firms.

Inversely, the advantage of the second scenario is that firm-specific differences will eventually be cancelled out after calculating the benchmark multiple. In order to select a set of comparable firms, Alford (1992) found that the rationale behind the choice of comparable firms within the same industry was correct and improved accuracy as the number of SIC digits increased, up to three digits. Furthermore, it was found that gains in accuracy were higher for larger firms (Alford, 1992).

Later, Liu *et al.* (2002) discovered that multiples-based valuation decreased in performance when all firms in the cross-section each year were used as comparable firms.

While we can select comparable firms based on their industry and achieve positive results (Alford, 19992 and Liu *et al.*, 2002), there is the disadvantage that industry might not be well defined. Studying more complex selection processes, Bhojraj and Lee (2002) found that comparable firms chosen according to future enterprise-value-to-sales and price-to-book ratios improved efficacy largely, relative to other techniques such as industry and size.

2.2.1.3 Computing the Benchmark Multiple

To complete the third step in multiples-based valuation, it is necessary to compute the benchmark multiple based on set of comparable firms according to one of four options:

$$Arithmetic\ Average = \frac{1}{n}\sum_{j=1}^{n}\frac{P_j}{VD_j} \tag{5}$$

$$Median = figure\ halfway\ between\ observed\ maximum\ and\ minimum \tag{6}$$

$$Weighted\ Average = \sum_{j=1}^{n}\left(\frac{VD_j}{\sum_{i=1}^{n}VD_i}\right)\times\frac{P_j}{VD_j} = \frac{\sum_{j=1}^{n}P_j}{\sum_{j=1}^{n}VD_j} \tag{7}$$

$$Harmonic\ Mean = \left(\frac{1}{n}\sum_{j=1}^{n}\frac{VD_j}{P_j}\right)^{-1} \quad (8)$$

Where VD_j and P_j denote respectively the value driver and price of the j^{th} comparable firm.

While arithmetic average is one of the most well known methods, its outliers exert considerable influence, originating overvalued figures. Consequently this makes it less suitable for accounting-based research, since this is an area where outliers are commonly found.

Nonetheless, alongside the median it is a method used often by analysts (Liu et al., 2007). However, it has been found that multiples-based valuation improved in performance when the harmonic mean was used, since it reduces the impact of small denominators (Liu et al., 2002).

2.2.2 Flows-Based Valuation Models

Flows-based models are based on the premise assumed by Francis *et al.* (2000): market value of a share equals the discounted value of the expected future payoffs generated by the share.

Furthermore they are in theory mathematically equivalent (Francis *et al.*, 2000 and Courteau *et al.*, 2006) and although obtaining the same results in practice may be difficult due to varying forecasted inputs, growth rates or discount rates (Francis *et al.*, 2000), certain authors claim it is a matter of care (Lundholm and O'Keefe, 2001).

2.2.2.1 Discounted Dividend Model (DIV)

Generally attributed to Williams (1938), the discounted dividend model states that a firm's equity is worth the sum of the discounted expected dividends to be received by shareholders over the life of the firm, being the terminal value equal to the liquidating dividend (Francis *et al.*, 2000):

$$Equity\ Value_F^{DIV} = \sum_{t=1}^{T}\frac{Expected\ Dividend_t}{(1+r_e)^t} \quad (9)$$

Where, r_e denotes cost of equity capital, F the valuation date and T the expected end date of the firm.

There are, however, special cases for which the formula above is slightly different. Firstly, if the firm pays the same dividend and is expected to have no end of life, the equation below is used:

$$Equity\ Value_t^{DIV} = \frac{Expected\ Dividend_{t+1}}{r_e} \tag{10}$$

On the other hand, if there is the same expectation concerning end of life but also it is predicted that the expected dividend will grow at a constant rate to infinity the formula is as below:

$$Equity\ Value_t^{DIV} = \frac{Expected\ Dividend_{t+1}}{r_e - growth\ rate} \tag{11}$$

Where the growth rate cannot be greater than the cost of equity capital.

The DIV and discounted cash-flow model (DCF) models are the backbone of accounting-based valuation models. All other techniques are developed from these two and changed to include accounting figures instead of cash measures such as dividend and FCF. Multiples-based valuation models share the same origin.

2.2.2.2 Discounted Cash-Flow Model (DCF)

The discounted cash-flow model consists in estimating a firm's cash-flows and discounting them by a rate corresponding to their risk level (Lie and Lie, 2002). Thus, the DCF technique is similar to DIV in its making, using FCF instead of dividends, since it assumes that FCF (*13*) represents with greater accuracy value added over a short horizon (Francis *et al.*, 2000), and replacing cost of equity capital with the weighted average cost of capital (*14*):

$$Enterprise\ Value_F^{DCF} = \sum_{t=1}^{T} \frac{FCF_t}{(1 + r_{WACC})^t} \tag{12}$$

$$FCF_t = NOPAT + Change\ in\ Net\ Operating\ Assets - Cash\ Investments \tag{13}$$

$$r_{WACC} = \omega_d \times (1 - \tau) \times r_d + \omega_{PS} \times r_{PS} + \omega_e \times r_e \tag{14}$$

Where τ denotes the corporate tax rate and $\omega_{d,PS,e}$ and $r_{d,PS,e}$ are respectively the proportions of debt, preferred stock and equity in the target capital structure and the cost of capital of each of the three mentioned sources.

2.2.2.3 Residual Income Model (RIM)

Emerging in literature in 1995 (Ohlson, 2005), the residual income model, or residual income valuation model (RIVM), is also a version of the DIV (Lee and Swaminathan, 1999). It can also be referred to as the Edwards-Bell-Ohlson (EBO) valuation technique (Frankel and Lee, 1998) depending on the approach chosen. Nonetheless, Ohlson (2005) argues that it should be relabelled as abnormal book values growth, since the model explains the market premium over book value by taking the present value of above or below benchmark increments in expected book values.

In essence, residual income is earnings that are left after charges for capital employed. From the equity perspective and then entity perspective we can mathematically define it as below:

$$Residual\ Income_t^e = Net\ Income_t - r_e \times BVE_{t-1} \tag{15a}$$

$$Residual\ Income_t^{e+d} = NOPAT_t - r_{WACC} \times NOA_{t-1} \tag{15b}$$

Where BVE denotes book value of equity and NOA net operating assets.

A key cornerstone of the RIM is that the clean surplus relationship (CSR) must be valid, i.e. the change in shareholders' equity is equal to net income less net dividends (Lundholm and O'Keefe, 2001):

$$BVE_t - BVE_{t-1} = Net\ Income_t - Dividend_t \tag{16a}$$

$$NOA_t - NOA_{t-1} = NOPAT_t - FCF_t \tag{16b}$$

This is a basic accounting concept according to which the balance sheet – items on the left side of the equation – relates to the income statement. However, in practice it might be difficult to validate this condition once GAAP's earnings paradigm violates clean surplus accounting, forcing one to assume expected values next to zero for dirty surplus items (Ohlson, 2005).

By rewriting the definition of dividend based on the equations above and then inserting it in the DIV we get the equity perspective of RIV (17a). Likewise, we can use the formulas above to change the definition of FCF and replace it in the DCF to get the entity perspective of RIV (17b). Both views are presented below:

$$Equity\ Value_t = BVE_t + \sum_{\tau=1}^{\infty} \frac{E_t[Residual\ Income_{t+\tau}^e]}{(1+r_e)^\tau} \tag{17a}$$

$$Enterprise\ Value_t = NOA_t + \sum_{\tau=1}^{\infty} \frac{E_t[Residual\ Income_{t+\tau}^{e+d}]}{(1+r_{WACC})^\tau} \tag{17b}$$

Looking at the traditional approach to RIM, the equity perspective (17a), it can be observed that company value is separated into two elements: capital invested (BVE) and the present value of all value created in the future (sum of future residual income) (Lee and Swaminathan, 1999).

As mentioned above, if the clean surplus relationship holds then the valuation calculated with the equations above must be equivalent to the DIV and DCF models. Besides, the RIM presents other interesting features, most notably dividend and accounting policy irrelevance. The former is due to the fact that dividend does not influence equity value and the latter to the CRS, which makes equity value independent of accounting policies (Francis *et al.*, 2000).

Finally, it should be last mentioned that Francis *et al.* (2000) found that RIM estimates showed higher accuracy relative to DIV or DCF and were able to explain 71% of the variation in prices. The authors claimed that this superiority might occur when distortions in book values are less severe than errors in estimating discount and growth rates or may be also due to greater predictability of residual income (Francis *et al.*, 2000).

2.2.2.3.1 Residual Income Model (RIM) Implementation Issues

In implementing the RIM, there are important issues to bring up. These include forecast horizons, earnings forecasts, dividend payout ratios, terminal values and cost of equity (Lee and Swaminathan, 1999).

The key to forecasting future residual income is to forecast earnings through return on equity (ROE), since book values can be obtained from CSR. Frankel and Lee (1998) used I/B/E/S consensus forecasts and found them to be highly correlated with current stock prices, being that RIM valuation explained more than 70% of cross-sectional variation in prices for their most recent observations.

Furthermore, in order to estimate long-term residual income there are two options: using analyst long-term growth forecasts (Frankel and Lee, 1998) or assume a gradual fade of ROE towards the long-term industry average (Lee and Swaminathan, 1999).

Regarding the forecast of book value, a payout ratio must be defined. The most recent one can be assumed. However, if there is a situation of dividend payout below zero this has no significance and if the ratio is above one, it should be assumed equal to one.

In order to obtain a value estimate, a terminal value (TV) is usually employed. It estimates the value of future residual income. Consequently, the traditional RIM from the equity perspective would be formulated as follows:

$$Equity\ Value_t = BVE_t + \sum_{\tau=1}^{T} \frac{E_t[Residual\ Income^e_{t+\tau}]}{(1+r_e)^\tau} + TV \qquad (18)$$

Where our forecast horizon is T and TV is calculated as below:

$$TV = \sum_{\tau=T+1}^{\infty} \frac{E_t[Residual\ Income^e_{t+\tau}]}{(1+r_e)^\tau} = \frac{E_t[Residual\ Income^e_{t+T}] \times (1+g_r)}{(1+r_e)^T \times (r_e - g_r)} \qquad (19)$$

Where g_r denotes growth rate.

Since the terminal value carries a large value in the equation, it should be carefully analysed to see if the underlying assumptions will not have a negative effect over the value estimate. One such case to look out for would be a negative terminal value.

Finally, concerning the calculation of cost of equity capital, it is performed with elements of the CAPM (Lee and Swaminathan, 1999):

$$r_e = r_f + \beta \times (r_m - r_f) \quad (20)$$

Where r_f is the risk free rate, β the firm's beta and r_m denotes the market return.

To determine the risk free rate, a short-term treasury bill or a long-term treasury bond can be used (Lee and Swaminathan, 1999). While for the firm's beta Thomson One Banker can provide a figure, the market return is indirectly determined by putting an arbitrary estimate on the market premium, which historically is around 5% (Lee and Swaminathan, 1999).

2.2.2.4 Abnormal Earnings Growth Model (AEGM)

Based on a mathematical construct equivalent to the RIM's, the abnormal earnings growth model (*21*) spins using two key concepts: near-term expected earnings per share (EPS) and its future growth (Ohlson and Juettner-Nauroth, 2005). On taking on these concepts, the AEGM, unlike the RIM, deals in semantics in which analysts are fluent, making Ohlson (2005) believe that the AEGM will replace the RIM.

$$Equity\ Value_t = \frac{E_t[NI_{t+1}]}{r_e} + \sum_{\tau=1}^{T} \frac{E_t[z_{t+\tau}]}{(1+r_e)^{\tau}} + \sum_{\tau=T+1}^{\infty} \frac{E_t[z_{t+\tau}]}{(1+r_e)^{\tau}} \quad (21)$$

Where NI stands for net income, or earnings, and

$$z_t = \frac{1}{r_e} \times \left(\Delta NI_{t+1} - r_e \times (NI_t - DIV_t)\right) \quad (22)$$

Where ΔNI_{t+1} is the variation of net income.

Comparing the AEGM (*21*) to its RIM equivalent (23), similarities are easily observed. Whereas the AEGM is anchored in capitalised next period net income, the RIM builds on top of current book value. Then both equations use a forecast horizon T and after that recur to a terminal value, which is less influent in the AEGM since its anchor seizes a higher percentage of the final valuation estimate than in the RIM.

$$Equity\ Value_t = BVE_t + \sum_{\tau=1}^{T} \frac{E_t[RI^e_{t+\tau}]}{(1+r_e)^{\tau}} + \sum_{\tau=T+1}^{\infty} \frac{E_t[RI^e_{t+\tau}]}{(1+r_e)^{\tau}} \quad (23)$$

Additionally, the AEGM is dividend policy independent, overcomes the RIM's dependence on the CSR while shifting focus to earnings, concepts around which equity valuation persistently revolves (Ohlson and Juettner-Nauroth, 2005). As Ohlson (2005) succinctly put it, the underlying idea is that ex-ante capitalised earnings approximate market value more closely than book values.

2.2.3 Conclusion on the Accounting-Based Valuation Models

Having discussed traditional valuation models it is now important to stress that these perform better with mature firms in established industries. The explanation behind that fact is that there is more information available and this provides a clear picture of the firm, allowing better estimates for model inputs.

With less stable and young companies the case is different. Furthermore, for specific industries there are less orthodox models that better explain value. This is due to the accounting treatment of fundamentals that are key in specific industries, for instance R&D or brand development (Amir and Lev, 1996).

In the case of bankruptcy, the lack of oversight makes multiples and cash-flow-based models imprecise, although unbiased, due to the limitation of available information (Gilson *et al.,* 2000).

The lack of information not only in bankruptcies, but also in IPOs makes it complicated to estimate cash-flows and consequently DCF performs poorly (Kim and Ritter, 1999 and Gilson *et al.*, 2000). Thus, Kim and Ritter (1999) recommend using multiples in such situations and found that forecasted earnings are more accurate than trailing earnings. In addition, Guo *et al.* (2005) found R&D expenditures a consistent financial value driver for Biotech IPOs and, as Amir and Lev (1996) before, discovered that nonfinancial information was an important and consistent value driver as well.

Burgstahler and Dichev (1997) present another model. The authors suggest a two-dimensional model which values not only the firm's in its current employment of resources but also its hypothetical employment of resources elsewhere.

2.3 Concluding Remarks on the Literature Review

This review was useful to see how accounting numbers were first linked to firm value (Ball and Brown, 1968). Moreover it was examined a key separation between flow-based and multiples-based valuation, where it was clear that multiples are easier to understand (Lie and Lie, 2002).

It was also understood that flow-based models while in theory should be equivalent (Francis *et al.*, 2000 and Courteau *et al.*, 2006), have in practice yielded differences in performance that favour the RIM (Francis *et al.*, 2000).

Finally, it was noted that these models function better with mature, established firms in stable external conditions. For particular situations, specific models can be applied with superior results.

Chapter 3: Large Sample Analysis

3.1 Introduction

3.1.1 Aim, Scope and Structure of the Large Sample Analysis

- ***Research Question:*** *Does a high ratio Price to Operating Income imply worse performance of P/E multiple and RIM based valuations?*

This chapter analyses whether a large gap between a firm's operational performance and its market price implies that valuation models are less accurate. It has been suggested in literature that a high P/OP makes it more difficult to link a firm's valuation with its accounting numbers (Trueman *et al.*, 2000). Thus, the aim of this chapter is to find if empirical evidence support the claim that a high Price to Operating Income (P/OI) translates into a worse performance of valuation models.

As a proxy for operational performance, Operating Income Before Depreciation (OIBDP) was selected since it best mirrors the firm's operational status quo, isolating influences that hide true operational performance. In the numerator of the abovementioned ratio lays the share price in April. The valuation models used for this study are the RIM and the Price-Earnings (P/E) multiple.

The following section presents the hypotheses developed and after the research design methodology is described. The final sections include the analysis of results and the concluding remarks.

3.1.2 Hypotheses Development

The hypotheses posited in this dissertation are derived from the rationale presented in chapter 1 and crafted by the insights retrieved from chapter 2:

- ***H1:*** *High Price to Operating Income implies poorer performance of valuation models, P/E Multiple and RIM, relative to low P/OI;*
- ***H2:*** *The level of performance is not equal across years;*
- ***H3:*** *The level of performance is not equal across industries;*
- ***H4:*** *The P/E multiples-based valuation model performs better than the RIM when applied to high P/OI firms.*

The first hypothesis (*H1*) is based on the difficulty of valuing firms which market price is well above its operating performance (Trueman *et al.*, 2000).

As economic conditions deteriorate, it is posited that the effect of poorer performance of valuation models will be exacerbated. This means that for years of economic crisis the average performance of valuations models is expected to be worse, resulting in performance differences across years (*H2*).

Similarly, it is expected that industries will be more or less exposed to the high P/OI effect due to industry-specific characteristics (*H3*).

Finally, since *H1* implies that accounting numbers are less connected to firm value in high P/OI companies, the RIM is expected to be a worse value predictor since it requires more fundamentals' input than the P/E, which better reflects the market valuation (*H4*).

3.2 Research Design

3.2.1 Sample Selection

The initial dataset contained 10,432 observations of U.S. firms with publicly traded common stocks between 2007-2012 [3]. Furthermore, these were nonfinancial firms[4] whose fiscal years ended in December. Adding to that, their share prices were at least $1 and they were followed by at least one analyst. Finally, total assets, revenues, number of shares outstanding, and the adjustment factor were positive.

The sample selection process is presented in table 1. The first criterion applied was that observations missing the median of 1 or 2-year-ahead earnings per share (EPS) forecasts (mdfy1 and mdfy2, respectively) or missing operating income before depreciation (OIBDP) were deleted. This was due to valuation model requirements and to enable the sample split into high and low P/OI.

The following step was to eliminate observations with less than 3 mdfy2 forecasts for its year and SIC3 code group in order to have a meaningful harmonic mean benchmark multiple at SIC3 level[5].

To guarantee that the cost of equity capital is computed with positive beta, 47 observations were withdrawn. Valuation model requirements forced the elimination of observations with non-positive EPS, BVE per share (BPS) or mdfy1 or mdfy2.

Then the final exclusion took place due to non-positive P/E estimates. Sample trimming followed with cut-off defined at 1% in order to eliminate extreme observations that would misrepresent the population.

The last stage consisted in the separation of the final sample (A) into high (A_H) and low (A_L) P/OI. It was defined that high P/OI was above the median of the ratio[6].

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[3] Fiscal years 2006-2011.

[4] SIC2 code groups were not 60-69.

[5] Since Alford (1992) showed that at such level performance is increased.

[6] Other options were considered such as setting high (low) above the third (below the first) quartile, but were not employed in order to keep a greater number of observations and consequently higher statistical power.

Additionally, two other samples of high and low P/OI were created: B[7] and C[8]. So that the median is significant, for C observations with less than six SIC3 group observations were excluded. Three different samples were created to verify if (and how) the analysis varies according to the definition of high/low P/OI.

Table 1 – Sample Selection Process		Number of Observations
Observations of U.S. public firms between 2007 and 2012		10432
Observations with missing median of 1 (mdfy1) or 2-year (mdfy2) ahead EPS forecasts or OIBDP (Op. Income Before Depr.)		(1897)
Observations with less than 3 mdfy2 forecasts for its year and SIC3 code group		(728)
Observations with missing or non-positive beta		(47)
Observations with non-positive book value of equity per share		(279)
Observations with non-positive earnings per share		(1316)
Observations with non-positive mdfy1 or mdfy2		(143)
Observations with non-positive P/E valuations		(87)
Observations trimmed with cut-off set at 1%		(672)
Final sample of U.S. public firms between 2007 and 2012		**5263**
A	Sub-sample A_H: high P/OI firms	2631
	Sub-sample A_L: low P/OI firms	2632
B	Sub-sample B_H: high P/OI firms	2630
	Sub-sample B_L: low P/OI firms	2633
Observations eliminated due to less than 6 firms present in SIC3 group		(65)
Final sample of U.S. public firms between 2007 and 2012		5198
C	Sub-sample C_H: high P/OI firms	2573
	Sub-sample C_L: low P/OI firms	2625

3.2.2 Data and Variable Definitions

The data for the original sample was retrieved from Compustat[9], I/B/E/S[10], and CRSP[11]. Table 2 lists the variables used in the large sample analysis[12]:

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7 Instead of using the whole sample's median, highs (lows) were defined as above (equal or below) the median P/OI of their year (sub-sample B).

8 The same process was applied but with the median P/OI of each SIC3 group (sub-sample C).

9 Compustat provides information regarding firms' reported accounting numbers.

Table 2 – Definition of Variables Used

Variable	Database	Type	Units	Description
ABSERROR_PE	N/A	Num	% of P4	Absolute Error of P/E Valuation Relative to P4
AE_VAL_RIVM	N/A	Num	% of P4	Absolute Error of RIM Valuation Relative to P4
AJEX	Compustat	Num	N/A	Adjustment Factor
AT	Compustat	Num	$ Millions	Total Assets
BETA	CRSP	Num	N/A	Market Beta Using Daily Returns
BPS	N/A	Num	$	Total Common Equity per Share (Adjusted with AJEX)
BPS1	N/A	Num	$	$BPS + MDFY1 \times (1 - \frac{DVC}{EPS})$ *(24)*
CEQ	Compustat	Num	$ Millions	Total Common Equity
CSHO	Compustat	Num	Millions	Common Shares Outstanding
CSHPRI	Compustat	Num	Millions	Common Shares Used to Calculate Earnings Per Share
CV	N/A	Num	$	$\frac{RI2/(KE-G)}{1+KE}$ *(25)*
DIFF_AE	N/A	Num	%	Difference in Absolute Errors Between the RIM and P/E multiple
DC_RI1	N/A	Num	$	Discounted RI1 at Cost of Equity Capital
DPAYOUT	N/A	Num	$	DVC/EPS *(26)*
DVC	Compustat	Num	$ Millions	Common Dividends
EP	N/A	Num	$	$MDFY2/P4$ *(27)*
EPS	N/A	Num	$	EPSPX Adjusted with AJEX
EPSPX	Compustat	Num	$ Millions	Earnings Per Share Excluding Extraordinary Items
FYEAR	Compustat	Num	N/A	Fiscal Year
G	N/A	Num	%	Assumed Growth Rate of 1.5% for RIM
HIGH	N/A	Num	N/A	Dummy that Equals 1 (0) if Observation is High (Low) P/OI
HMEAN_PE	N/A	Num	$	Harmonic Mean of Yearly, SIC3 Comparables' P/E
KE	N/A	Num	N/A	Average Cost of Equity Capital of whole sample (r_e)

[10] I/B/E/S provides analyst forecasts and market prices.
[11] CRSP divulges annual betas.
[12] In appendix are listed all variables in the database (table 22).

MDFY1	I/B/E/S	Num	$	Median of 1-Year-Ahead EPS Forecasts
MDFY2	I/B/E/S	Num	$	Median of 2-Year-Ahead EPS Forecasts
NI	Compustat	Num	$ Millions	Net Income (Loss)
OIBDP	Compustat	Num	$ Millions	Operating Income Before Depreciation
P4	I/B/E/S	Num	$	Share Price in April
PE	N/A	Num	$	$P4/MDFY2$ *(28)*
PRICETOOI	N/A	Num	$	$P/OI = P4/\left(\frac{OIBDP}{CSHPRI \times AJEX}\right)$ *(29)*
RI1	N/A	Num	$	$MDFY1 - KE \times BPS$ *(30)*
RI2	N/A	Num	$	$MDFY2 - KE \times BPS1$ *(31)*
SE_VAL_RIVM	N/A	Num	% of P4	Signed Error of RIM Valuation Relative to P4
SERROR_PE	N/A	Num	% of P4	Signed Error of P/E Valuation Relative to P4
SIC3	Compustat	Num	N/A	3-Digit SIC
V_HMEAN_PE	N/A	Num	$	P/E Value Estimate *(3)* using Harmonic Mean *(8)*
VAL_RIVM	N/A	Num	$	RIM Value Estimate *(18)*

Since I/B/E/S data is already adjusted for stock split/dividend, Compustat items were also adjusted as generalised below[13]:

$$Adjusted\ Variable\ Per\ Share = \frac{Unadjusted\ Variable\ (Total)}{CSHO \times AJEX} \quad (32a)$$

$$Adjusted\ Variable\ Per\ Share = \frac{Unadjusted\ Variable\ (Total)}{CSHPRI \times AJEX} \quad (32b)$$

3.2.3 Research Methods

3.2.3.1 Residual Income Model (RIM)

The RIM (*33*)[14] was chosen since it is superior in performance relative to DIV or DCF (Francis *et al.*, 2000).

$$VAL\_RIVM = BPS + \frac{RI1}{1 + KE} + \frac{RI2/(KE - G)}{1 + KE} \quad (33)$$

[13] It should be noted that *32a* is used for balance sheet variables, whereas *32b* is employed with income or cash flow statement items.
[14] Based on equations *18* and *19.*

Where KE is the sample's average cost of equity capital computed as per equation *20* using a risk free rate determined, as hypothesised by Lee and Swaminathan (1999), by the yearly average of 90-day annualised T-Bills. The market premium was set at 5% (Lee and Swaminathan, 1999) and beta comes from CRSP.

Furthermore, RI1 (*30*) and RI2 (*31*) are calculated with I/B/E/S median forecasts since they were found to be highly correlated with stock prices (Frankel and Lee, 1998) and avoid the effect of extreme values.

Concerning the dividend payout rate (*26*), for the extreme case when the last reported ratio is above 1, DPAYOUT is set equalling 1 (Lee and Swaminathan, 1999). When EPS are negative, dividend payout is set to equal the average return of the firm's assets (*34*)[15] (Lee and Swaminathan, 1999).

$$DPAYOUT = \frac{DVC}{0.05 \times AT} \tag{34}$$

3.2.3.2 Price to Earnings Multiple (P/E)

In order to perform a multiples-based valuation, the P/E was selected:

$$V\_HMEAN\_PE = MDFY2 \times HMEAN\_PE \tag{35}$$

The 2-year-ahead median forecast was chosen as value driver for its explanatory power (Liu *et al.*, 2002) and for reducing the influence of extreme outliers.

Comparable firms are those within the same SIC3 group code (Alford, 1992) and fiscal year and the benchmark multiple was computed using an harmonic mean (*8*) since it increases performance (Liu *et al.*, 2002).

3.2.3.3 Performance Measures

Performance is measured according to valuation errors. While valuation bias is shown by signed valuation errors (SE) (*36*), absolute valuation errors (AE) (*37*) denote inaccuracy. By bias it is meant a tendency to consistently over (negative SE) or underestimate (positive SE) a firm's value and by inaccuracy[16] it is understood the distance of the value estimate to market price. Both are measured in percentage of price.

$$Signed\ Error = \frac{Price - Value\ Estimate}{Price} \tag{36}$$

[15] Where 0.05 represents the market premium of 5%.

[16] Its antonym, accuracy, denotes the adjacency of the value estimate to market price.

$$Absolute\ Error = \frac{|Price - Value\ Estimate|}{Price} \quad (37)$$

3.3 Descriptive Statistics

3.3.1 General Descriptive Statistics

Below, table 3 lists the descriptive statistics for sample A. It comprises 5263 observations, split into 2631 high P/OI and 2632 low P/OI observations[17], across 140 SIC3 groups and six fiscal years, 2006-2011. Observations are distributed across fiscal years as can be observed below in table 4:

Table 4 – Observations per Fiscal Year

2006	1011
2007	965
2008	710
2009	804
2010	900
2011	873
Total	5263

Furthermore, Samples B and C are used to determine if the classification of high/low P/OI under a multi-period, multi-industry pooled sample[18] yields the same results as a classification under an intra-period[19] or intra-industry[20] perspective. From the analysis of each sample's descriptive statistics it is possible to infer that they are very similar and, consequently, high/low P/OI is a coherent, firm-specific classification across years and industry[21].

[17] The difference in number of observations between high and low P/OI is justified by the criteria applied to determine such classification; below or equal to the median are low observations. Consequently, with an odd number of total observations, the low sub-sample is greater than its high counterpart by one.

[18] Sample A, see table 3 for descriptive statistics.

[19] Sample B, see table 23 in appendix for descriptive statistics.

[20] Sample C, see table 24 in appendix for descriptive statistics.

[21] The only visible difference resulting from the contrasting of the descriptive statistics of samples A with those of samples B and C is a slight tendency of sample C to reduce the clarity of distinguishable high vs. low P/OI differences, except in share price (P4). A possible explanation is that classifying firms as high/low P/OI within SIC3 groups includes the risk of classifying a firm *X* as high relative to a low P/OI firm *Y* that has higher P/OI but belongs to another SIC3 group.

Table 3 - Sample A Descriptive Statistics

Panel A: Pooled Sample A	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	5263	30.1769	19.9570	25.7900	2.7800	15.2100	40.3300	132.6000
Common Equity per Share (BPS)	5263	12.7892	8.9095	10.6262	0.6791	6.0887	17.3554	54.8257
EPS Excl. Extraordinary Items (EPS)	5263	1.6969	1.4105	1.3300	0.0350	0.6800	2.2900	10.2300
Price to OIBDP (P/OI)	5263	10.0788	8.3102	7.8107	1.5111	5.2594	11.7868	73.5345
Median 1-Year-Ahead EPS (MDFY1)	5263	1.8560	1.3367	1.5200	0.0100	0.8500	2.5300	8.4100
Median 2-Year-Ahead EPS (MDFY2)	5263	2.1592	1.4582	1.8000	0.1500	1.0500	2.9000	8.1800

Panel B: Sub-Sample A_L	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2632	27.0015	17.0008	23.5000	2.7800	14.4100	36.4000	112.6800
Common Equity per Share (BPS)	2632	15.1810	9.6126	13.2656	0.8591	7.8245	20.5738	54.8257
EPS Excl. Extraordinary Items (EPS)	2632	2.0062	1.5489	1.6300	0.0350	0.8900	2.7000	10.2300
Price to OIBDP (P/OI)	2632	5.1243	1.6028	5.2595	1.5111	3.8706	6.4378	7.8107
Median 1-Year-Ahead EPS (MDFY1)	2632	2.0190	1.3929	1.7000	0.0100	0.9800	2.7200	8.4100
Median 2-Year-Ahead EPS (MDFY2)	2632	2.2877	1.4754	1.9500	0.1800	1.1800	3.0400	8.1800

Panel C: Sub-Sample A_H	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2631	33.3534	22.0804	27.9900	2.9100	16.5300	45.3100	132.6000
Common Equity per Share (BPS)	2631	10.3964	7.4114	8.5540	0.6791	4.9824	13.6124	50.4788
EPS Excl. Extraordinary Items (EPS)	2631	1.3876	1.1785	1.0600	0.0400	0.5200	1.9100	9.3800
Price to OIBDP (P/OI)	2631	15.0353	9.2984	11.7868	7.8146	9.4563	16.7245	73.5345
Median 1-Year-Ahead EPS (MDFY1)	2631	1.6930	1.2573	1.3500	0.0200	0.7500	2.3400	6.6600
Median 2-Year-Ahead EPS (MDFY2)	2631	2.0307	1.4296	1.6600	0.1500	0.9500	2.7500	7.5600

Sample A has some degree of skewness, as the mean is consistently higher than the median. This is a result of the sample selection process, in which many variables had their minimum set at above zero while maximums were not as limited, resulting in a greater influence of large positive values.

High P/OI observations have a higher average P4 than their low counterparts. This can mean that although investors attribute a higher value to high P/OI firms, they do so due to factors unrelated to operational performance.

EPS is in turn lower in A_H. Since it is the end product of operating income, this feature is a consequence of the sub-sample separation. This remark is also valid for the abovementioned price superiority.

Regarding BPS, it is curious to observe that the investment in firm equity is smaller in high P/OI, although the average market price of these firms is higher. This implies that the market expects a higher return on equity for high P/OI.

Finally, it is curious to note that for samples A and B median EPS forecasts are slightly lower for the A_H, although this effect is neutralised in sample C. While for A and B this reflects caution in the estimation, for C the fact the inexistence of differences may imply that short-term forecasts are similar within SIC3 groups.

3.3.2 Descriptive Statistics by Fiscal Year[22]

Additionally, a yearly breakdown of mean and median was performed[23]. Using P4 and median EPS forecasts, it can be detected an economic downturn from 2006-2008 and a positive cycle from 2009 onwards.

Table 5 - Sample A Descriptive Statistics By Fiscal Year

Pooled Sample A	**2006**		**2007**		**2008**		**2009**		**2010**		**2011**	
	Mn	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**
Share Price in April (P4)	33.0	28.1	29.8	24.1	22.7	19.1	29.4	26.3	32.7	28.1	31.6	27.1
Common Equity per Share (BPS)	11.8	9.9	12.3	10.3	12.8	10.8	12.8	10.4	13.4	11.2	13.7	11.4
EPS Excl. Extraordinary Items (EPS)	1.7	1.4	1.7	1.3	1.9	1.5	1.5	1.1	1.6	1.3	1.8	1.5
Price to OIBDP (P/OI)	11.7	9.6	10.4	7.9	7.4	5.4	10.5	8.2	10.3	8.1	9.4	7.3
Median 1-Year-Ahead EPS (MDFY1)	1.8	1.5	1.9	1.5	1.6	1.3	1.7	1.4	2.0	1.7	2.1	1.8
Median 2-Year-Ahead EPS (MDFY2)	2.1	1.7	2.2	1.8	1.9	1.6	2.0	1.7	2.3	2.0	2.4	2.0

[22] For reference, a breakdown by SIC3 can also be analysed in appendix in table 25.
[23] Mean and median respectively referred to as Mn and Md.

3.4 Data Analysis

3.4.1 Signed and Absolute Valuation Errors

3.4.1.1 Descriptive Statistics

3.4.1.1.1 General Descriptive Statistics

To evaluate the performance of each valuation model, signed (SE) and absolute (AE) valuation errors are used. Since similarities between samples A, B, and C have been established, the focus will henceforth be on sample A.

The first striking feature visible from table 6 is that both models appear to be almost equally positively biased[24] and inaccurate. The minimum is in absolute terms largely superior to the maximum, which explains positive bias since there are apparently large negative extreme values influencing SE. This skewness is also visible in the differences between mean and median bias.

High P/OI firms have more accurate and less biased value estimates. In fact, they are slightly negatively biased whereas A_L shows tendency towards overestimation.

Positive bias in A_H is essentially visible in RIM SE since the P/E's show that this model is virtually unbiased for high P/OI firms. However, both models are equally inaccurate within each sub-sample. This model equality is more evident in A_L, where bias and inaccuracy are both similar between models.

It should finally be noted that valuation errors are more volatile for both models in the low P/OI sub-sample, implying larger poor performances here. These contrasts between A_H and A_L are surprising and go against what was expected (*H1*).

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[24] It should be remembered that bias is positive (negative) when signed errors are negative (positive) due to overestimation (underestimation), as per equation *(36)*.

Table 6 - Sample A Descriptive Statistics

Panel A: Pooled Sample A	N	Mean	Standard Deviation	Median	Minimum	Q1	Q3	Maximum
P/E Signed Error (SERROR_PE)	5263	-0.1096	0.4340	-0.0349	-2.6551	-0.2740	0.1628	0.6996
P/E Absolute Error (ABSERROR_PE)	5263	0.3048	0.3278	0.2123	0.0001	0.0943	0.3965	2.6551
RIM Signed Error (SE_VAL_RIVM)	5263	-0.1040	0.4169	-0.0391	-1.8930	-0.3098	0.1758	0.6806
RIM Absolute Error (AE_VAL_RIVM)	5263	0.3136	0.2936	0.2353	0.0002	0.1075	0.4254	1.8930

Panel B: Sub-Sample A_L	N	Mean	Standard Deviation	Median	Minimum	Q1	Q3	Maximum
P/E Signed Error (SERROR_PE)	2632	-0.2273	0.4652	-0.1206	-2.6551	-0.3948	0.0600	0.6879
P/E Absolute Error (ABSERROR_PE)	2632	0.3413	0.3893	0.2100	0.0001	0.0917	0.4316	2.6551
RIM Signed Error (SE_VAL_RIVM)	2632	-0.2874	0.4284	-0.2086	-1.8930	-0.5137	0.0115	0.6704
RIM Absolute Error (AE_VAL_RIVM)	2632	0.3754	0.3537	0.2603	0.0002	0.1169	0.5216	1.8930

Panel C: Sub-Sample A_H	N	Mean	Standard Deviation	Median	Minimum	Q1	Q3	Maximum
P/E Signed Error (SERROR_PE)	2631	0.0082	0.3643	0.0563	-2.5927	-0.1601	0.2444	0.6996
P/E Absolute Error (ABSERROR_PE)	2631	0.2683	0.2465	0.2148	0.0007	0.0961	0.3693	2.5927
RIM Signed Error (SE_VAL_RIVM)	2631	0.0794	0.3112	0.1050	-1.7494	-0.0929	0.2993	0.6806
RIM Absolute Error (AE_VAL_RIVM)	2631	0.2518	0.1993	0.2120	0.0002	0.1005	0.3584	1.7494

3.4.1.1.2 Descriptive Statistics by Fiscal Year and SIC3

Again, valuation errors were broke down by fiscal year and SIC3[25] to check for trends.

Table 7 shows that in 2008 both models present worse accuracy. It is visible that RIM mean signed errors are more volatile, as are its absolute errors. This contrasts with the standard deviation presented in panel A of table 6, which did not show a significant difference.

[25] Table 28, see in appendix.

Regarding the SIC3 breakdown, it is clear how industries react differently to valuation models. Concluding, the analysis on valuation errors' descriptive statistics motivates a positive outlook towards the validation of the following hypotheses:

- ***H2:*** *The level of performance is not equal across years;*
- ***H3:*** *The level of performance is not equal across industries.*

Table 7 - Sample A Descriptive Statistics By Fiscal Year

Pooled Sample A	**2006**		**2007**		**2008**		**2009**		**2010**		**2011**	
	Mn	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**	**Mn**	**Md**
P/E SE	-0.100	-0.045	-0.108	-0.029	-0.131	-0.053	-0.135	-0.049	-0.100	-0.019	-0.091	-0.033
P/E AE	0.246	0.173	0.305	0.192	0.365	0.261	0.315	0.214	0.314	0.224	0.305	0.222
RIM SE	0.066	0.108	-0.121	-0.058	-0.269	-0.231	-0.044	-0.012	-0.090	-0.045	-0.218	-0.147
RIM AE	0.252	0.205	0.300	0.220	0.420	0.327	0.282	0.219	0.287	0.210	0.371	0.275

3.4.1.2 Statistical Tests

3.4.1.2.1 Test on the Accuracy and Bias of Valuation Models

The first test is performed on sample A as well as on both sub-samples. A parametric test - t-test - and a non-parametric test - Wilcoxon signed rank – are performed on the mean and median of signed and absolute valuation errors in order to find if the valuation error has a mean or median value of zero[26].

The correspondent hypotheses are best described as such:

T-Test	**Wilcoxon Signed Rank**
$H_0: Mean\ Valuation\ Error = 0$	$H_0: Median\ Valuation\ Error = 0$
$H_1: Mean\ Valuation\ Error \neq 0$	$H_1: Median\ Valuation\ Error \neq 0$

Where H_0 and H_1 stand for the null and alternative hypotheses, respectively.

Table 8 shows that for nearly all tests the null hypotheses are rejected at the significance level of 5%[27]. This means that for all cases, except one, it is accepted that models are biased and inaccurate.

However, this is not extended to one situation. Under no traditional significance level it is rejected that the P/E multiple is unbiased for the A_H. Despite this exception, the tests largely conclude what was expected: valuation models are, to a degree, biased and inaccurate.

[26] I.e. there is no error and model is unbiased and entirely accurate.

[27] Henceforth used as the default significance level. Other significance levels that will be referred to as traditional significance levels are 10% and 15%.

Table 8 – Test on the Accuracy and Bias of Valuation Models

Panel A: Pooled Sample A	**N**	**Mean**	**P-Value**	**Median**	**P-Value**
P/E Signed Error (SERROR_PE)	5263	-0.1096	<0.0001	-0.0349	<0.0001
P/E Absolute Error (ABSERROR_PE)	5263	0.3048	<0.0001	0.2123	<0.0001
RIM Signed Error (SE_VAL_RIVM)	5263	-0.1040	<0.0001	-0.0391	<0.0001
RIM Absolute Error (AE_VAL_RIVM)	5263	0.3136	<0.0001	0.2353	<0.0001

Panel B: Sub-Sample A_L	**N**	**Mean**	**P-Value**	**Median**	**P-Value**
P/E Signed Error (SERROR_PE)	2632	-0.2273	<0.0001	-0.1206	<0.0001
P/E Absolute Error (ABSERROR_PE)	2632	0.3413	<0.0001	0.2100	<0.0001
RIM Signed Error (SE_VAL_RIVM)	2632	-0.2874	<0.0001	-0.2086	<0.0001
RIM Absolute Error (AE_VAL_RIVM)	2632	0.3754	<0.0001	0.2603	<0.0001

Panel C: Sub-Sample A_H	**N**	**Mean**	**P-Value**	**Median**	**P-Value**
P/E Signed Error (SERROR_PE)	2631	0.0082	0.2472	0.0563	<0.0001
P/E Absolute Error (ABSERROR_PE)	2631	0.2683	<0.0001	0.2148	<0.0001
RIM Signed Error (SE_VAL_RIVM)	2631	0.0794	<0.0001	0.1050	<0.0001
RIM Absolute Error (AE_VAL_RIVM)	2631	0.2518	<0.0001	0.2120	<0.0001

3.4.1.2.2 Test on the Equality of Accuracy and Bias Across Sub-Samples

Although some considerations regarding differences in valuation model performance between A_H and A_L have been deduced from the descriptive statistics of valuation errors, it is important to perform an empirical verification of the following:

T-Test

$$H_0: Mean\ Valuation\ Error\ A_L = Mean\ Valuation\ Error\ A_H$$
$$H_1: Mean\ Valuation\ Error\ A_L \neq Mean\ Valuation\ Error\ A_H$$

Wilcoxon Signed Rank

$$H_0: Median\ Valuation\ Error\ A_L = Median\ Valuation\ Error\ A_H$$
$$H_1: Median\ Valuation\ Error\ A_L \neq Median\ Valuation\ Error\ A_H$$

The results confirmed what had previously been concluded. Table 9 shows that the null hypotheses of equality of means or medians are rejected.

Although mean differences are higher, medians are close. This implies that A_L is more heavily influenced by extreme observations in what concerns valuation errors, especially SE.

Table 9 – Test of Equality of Means and Medians

Panel A: Pooled Sample A	Mean Valuation Error			Median Valuation Error		
	A_L	A_H	P-Value	A_L	A_H	P-Value
P/E Signed Error (SERROR_PE)	-0.2273	0.0082	<0.0001	-0.1206	0.0563	<0.0001
P/E Absolute Error (ABSERROR_PE)	0.3413	0.2683	<0.0001	0.2100	0.2148	0.0210
RIM Signed Error (SE_VAL_RIVM)	-0.2874	0.0794	<0.0001	-0.2086	0.1050	<0.0001
RIM Absolute Error (AE_VAL_RIVM)	0.3754	0.2518	<0.0001	0.2603	0.2120	<0.0001

The Satterthwaite method was used to test the means since variances were found to be unequal.
A two-sided test with normal approximation was used to test the medians.

3.4.1.2.2 Test on the Equality of Accuracy and Bias Across Valuation Models

Having seen that both models are inaccurate, it is interesting now to compare them and verify if they are equally inaccurate. Table 10 presents the average and median difference between both models' AE. To this purpose, a new variable was created:

$$DIFF\_AE = AE\_VAL\_RIVM - ABSERROR\_PE \tag{38}$$

Thus, the hypotheses for these tests are similar to those in 3.4.1.2.1:

T-Test	Wilcoxon Signed Rank
$H_0: Mean\ DIFF\_AE = 0$	$H_0: Median\ DIFF\_AE = 0$
$H_1: Mean\ DIFF\_AE \neq 0$	$H_1: Median\ DIFF\_AE \neq 0$

Table 10 – Test of Equality of Valuation Models

Panel A: Pooled Sample A	N	Mean	P-Value	Median	P-Value
RIM AE - P/E AE (AE_VAL_RIVM - ABSERROR_PE)	5263	0.0089	0.0510	0.0175	<0.0001

Panel B: Sub-Sample A_L	N	Mean	P-Value	Median	P-Value
RIM AE - P/E AE (AE_VAL_RIVM - ABSERROR_PE)	2632	0.0341	<0.0001	0.0292	<0.0001

Panel C: Sub-Sample A_H	N	Mean	P-Value	Median	P-Value
RIM AE - P/E AE (AE_VAL_RIVM - ABSERROR_PE)	2631	-0.0164	0.0005	0.0088	0.7082

Regarding the pooled sample H_0 is rejected for the median, but for the mean it is only rejected at a 10% significance level. Thus, the RIM is on average slightly less accurate.

In A_L differences are more visible and model accuracy equality is rejected, as the P/E is more accurate. Equality of means is also rejected for A_H, but equality of medians is validated. In this sub-sample the RIM is slightly more accurate, unlike before.

Overall, it is visible that differences are quite small between the accuracy of each model and it is also clear that they are larger in the small P/OI sub-sample.

3.4.1.2.3 Equality of Value Estimates Across Fiscal Years and SIC3 Groups

The ANOVA procedure was applied to sample A and both sub-samples. This procedure tested whether the mean value estimates from both models were equal throughout all fiscal years or all SIC3 groups:

$$H_0: Mean\ Value\ Estimate_{m,j,2006} = \cdots = Mean\ Value\ Estimate_{m,j,f}$$
$$H_1: At\ least\ one\ mean\ value\ estimate\ is\ different$$

$$H_0: Mean\ Value\ Estimate_{m,j,104} = \cdots = Mean\ Value\ Estimate_{m,j,s}$$
$$H_1: At\ least\ one\ mean\ value\ estimate\ is\ different$$

Where m, j, f, and s stand for the two valuation methods, the three sample and sub-samples, the various fiscal years, and the various SIC3 group codes, respectively.

The results were as expected and unequivocally rejected all but one null hypothesis. It was accepted that P/E bias is equal across all periods, although not equally accurate. Despite this one exception, it is possible to conclude that mean value estimates vary according to both SIC3 group and fiscal year.

Table 11 – Test on the Equality of Means Across Fiscal Years and SIC3 Groups

Panel A: Pooled Sample A		**N**	**P-Value**
Across Fiscal Years	P/E Signed Error (SERROR_PE)	5263	0.2103
	P/E Absolute Error (ABSERROR_PE)	5263	<0.0001
	RIM Signed Error (SE_VAL_RIVM)	5263	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	5263	<0.0001
Across SIC3 Groups	P/E Signed Error (SERROR_PE)	5263	<0.0001
	P/E Absolute Error (ABSERROR_PE)	5263	<0.0001
	RIM Signed Error (SE_VAL_RIVM)	5263	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	5263	<0.0001

Panel B: Sub-Sample A_L		**N**	**P-Value**
Across Fiscal Years	P/E Signed Error (SERROR_PE)	2632	0.0232
	P/E Absolute Error (ABSERROR_PE)	2632	0.0001
	RIM Signed Error (SE_VAL_RIVM)	2632	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	2632	<0.0001
Across SIC3 Groups	P/E Signed Error (SERROR_PE)	2632	<0.0001
	P/E Absolute Error (ABSERROR_PE)	2632	<0.0001
	RIM Signed Error (SE_VAL_RIVM)	2632	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	2632	<0.0001

Panel C: Sub-Sample A_H		**N**	**P-Value**
Across Fiscal Years	P/E Signed Error (SERROR_PE)	2631	<0.0001
	P/E Absolute Error (ABSERROR_PE)	2631	<0.0001
	RIM Signed Error (SE_VAL_RIVM)	2631	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	2631	0.0002
Across SIC3 Groups	P/E Signed Error (SERROR_PE)	2631	<0.0001
	P/E Absolute Error (ABSERROR_PE)	2631	<0.0001
	RIM Signed Error (SE_VAL_RIVM)	2631	<0.0001
	RIM Absolute Error (AE_VAL_RIVM)	2631	<0.0001

3.4.2 Explanatory Power of Valuation Models

In addition to the previous tests, an OLS regression is applied to each model in order to test how well market price (P4) is explained. The model sets as the dependent variable price (P4) and the independent variable is each model's value estimate[28]:

$$P4_{ij} = \alpha + \beta \times Value\ Estimate_{ij} + \varepsilon_{ij} \quad (39)$$

Where *i* and *j* denote respectively each observation and samples/sub-samples[29].

[28] VAL_RIVM and V_HMEAN_PE, as in table 2.
[29] A, A_H, and A_L.

The results obtained are presented in table 13 and attest to the better performance of the RIM, which is consistently superior to the P/E multiple in every sample/sub-sample. It is able to explain more than 70% of the share's market price and performs slightly better with low P/OI firms. This is also true for the P/E multiple, although only even more slightly. These results contrast with valuation error analysis, which showed that both models were more accurate with high P/OI firms.

It should also be noted that both models present good explanatory power, both being able to consistently explain at least nearly 70% of market price.

Table 12 – Regression Results

Panel A: Pooled Sample A	**N**	**Slope**	**P-Value**	**Adjusted R^2**
P/E Multiple (MDFY2)	5263	0.7614	<0.0001	0.6937
Residual Income Model (RIM)	5263	0.7440	<0.0001	0.7056

Panel B: Sub-Sample A_L	**N**	**Slope**	**P-Value**	**Adjusted R^2**
P/E Multiple (MDFY2)	2632	0.6912	<0.0001	0.7141
Residual Income Model (RIM)	2632	0.6581	<0.0001	0.7648

Panel C: Sub-Sample A_H	**N**	**Slope**	**P-Value**	**Adjusted R^2**
P/E Multiple (MDFY2)	2631	0.8170	<0.0001	0.7134
Residual Income Model (RIM)	2631	0.8596	<0.0001	0.7579

3.5 Concluding Remarks on the Large Sample Analysis

Initially, descriptive statistics demonstrated that classifying a company as high or low P/OI is a coherent classification within specific periods and SIC3 groups, since samples A, B, and C presented very similar statistics. Thus, the conclusions presented are robust against the P/OI classification.

Descriptive statistics of valuation errors showed that there was a yearly change in bias and accuracy, particularly evident in years of economic crisis, represented by the observations in the fiscal year of 2008 when valuation models were clearly less accurate. Moreover, the ANOVA test performed rejected the hypothesis of equality between yearly means across all sample/sub-samples in all but one case: P/E multiple signed errors in the pooled sample A. Therefore, in what concerns *H2* it is possible to validate the rationale presented previously:

- ***H2:*** *The level of performance is not equal across years*

The same test rejected the hypothesis of equality of SIC3 group valuation error means and consequently validated *H3*:

- ***H3:*** *The level of performance is not equal across industries*

Regarding *H4*, it was seen in descriptive statistics that the P/E multiple provides a less biased, although similarly accurate, valuation relative to RIM value estimates within the high P/OI sub-sample. Furthermore, it was empirically proved that the P/E multiple is an unbiased model when applied to high P/OI firms. Contrary to what the descriptive statistics revealed, the OLS regression exhibited a 4% negative difference in explanatory power between the P/E multiple and the RIM. With this in mind, it can be stated that there was a validation of P/E superior performance with high P/OI observations, but only in regards to valuation bias. The analysis on accuracy was inconclusive and, contrary to what was expected, it was proved that the RIM explains to a higher percentage the market price of a share.

- ***H4:*** *The P/E multiples-based valuation model performs better than the RIM when applied to high P/OI firms*

Finally, in order to answer the research question it also useful to bring up *H1*:

- ***Research Question:*** *Does a high ratio Price to Operating Income imply worse performance of P/E multiple and RIM based valuations?*
- ***H1:*** *High Price to Operating Income implies poorer performance of valuation models, P/E Multiple and RIM, relative to low P/OI*

Being synonymous, it is possible to answer both at once. It was seen that the high P/OI sub-sample had lower absolute and signed valuation errors, being valuation models more accurate and less biased when applied to A_H. It was also interesting to find that value estimates were positively biased for the low sub-sample, but both models either were unbiased or underestimated the share price of high P/OI firms. While the former is consistent with the optimism described by Beckers *et al.* (2004), the latter is more surprising. A possible explanation is that analysts are more cautious in predicting future earnings for firms that have a bigger gap between share price and operational performance, as was visible with the lower mean mdfy1 and mdfy2 for A_H.

Furthermore, the hypotheses of sub-samples A_H and A_L having equal mean or median valuation errors were rejected. Adding to that, the OLS regression showed that there was an overall satisfactory explanatory power, with valuation models in the high P/OI sub-sample performing slightly worse. In conclusion, the results indicate a rejection of *H1* and, consequently, a negative answer to the research question. It is concluded that a high price to operating income does not implicate a worse performance of the P/E multiple and/or RIM relative to low P/OI.

Lower 1 and 2-year-ahead earnings estimate may imply that analysts are more cautious with firms that have their share price less close to their operational performance. In addition to that, low P/OI have a lower average share price, which means that the P/E value estimate is more prone to overvalue this type of firm.

Regarding the lower performance of the RIM, it can be explained by the higher mean book value of low P/OI, which despite reducing future residual income and terminal value still exerts too high an influence in the final outcome of creating a higher average valuation for A_L (see table 13 below). Naturally, if this sub-sample has a lower average share price that leads to gross overvaluation as was clear from the analysis of descriptive statistics.

Table 13 – Descriptive Statistics of Key RIM Variables

		N	**Mean**	**Median**
Common Equity per Share (BPS)	Sub-Sample AH	2631	10.3964	8.5540
	Sub-Sample AL	2632	15.1810	13.2656
Discounted 1-Year-Ahead Residual Income (DC_RI1)	Sub-Sample AH	2631	0.7975	0.5741
	Sub-Sample AL	2632	0.7449	0.5064
RIM Terminal Value (CV)	Sub-Sample AH	2631	19.0094	13.5530
	Sub-Sample AL	2632	17.4706	11.7721

Chapter 4: Small Sample Analysis

4.1 Introduction

4.1.1 Aim, Scope and Structure of the Small Sample Analysis

- ***Research Question:*** *Is analyst treatment of high Price to Net Income (P/NI) firms different from their treatment of low P/NI companies?*

This chapter will look into the hypothesis that analysts provide a different treatment for firms with a high ratio Price to Net Income per share (P/NI). Relative to the large sample analysis one important element has changed. The sample split is now implemented based on the P/NI ratio rather than P/OI. The point is to use a slightly different perspective from the previous chapter, where now it is looked at a firm's overall performance and not only its operational performance.

As in the large sample analysis, this chapter is deeply motivated by Trueman *et al.* (2000), who wrote of an analyst that alleged he could justify any Amazon.com share price between $1 and $200 by changing his assumptions. Likewise, it is intended to understand how analysts operate in terms of financial analysis with high price to bottom line performance firms relative to those which can more closely link their share price with its fundamentals.

First, the sample selection process will be described in order to increase the transparency of this analysis. This will be followed by the main analysis to valuation models used by analysts and their issued recommendations. To complement and add information, supplementary tests will be performed as well. Lastly, a conclusion will summarise key findings.

4.1.2 Hypotheses Development

The small sample analysis is preceded by the presentation of important hypotheses inspired by chapters 1 and 2:

- ***H1:*** *Multiple-based valuation is the most common method used by analysts;*
- ***H2:*** *H1 is even more evident in high P/NI firms;*
- ***H3:*** *Analysts are more optimistic, i.e. have more buy recommendations, with high Price to Net Income firms;*
- ***H4:*** *Analysts use a longer forecast horizon for high P/NI firms;*
- ***H5:*** *Nonfinancial information is more useful for high P/NI firms.*

Demirakos *et al.* (2004) found that multiples-based valuation is the most common technique employed by analysts. Thus, it is expected that this finding be verified in this dissertation (*H1*).

The rationale on which this study is founded is that high price to accounting-based performance firms are more disconnected from their accounting numbers. Consequently, it is posited that *H1* will be more evident in the sub-sample high P/NI, since the use of multiples-based relative to flow-based valuation implies that market figures provide a better value estimate than accounting ones (*H2*).

As Beckers *et al.* (2004) found, analysts tend to be positively biased in their recommendations. It is hypothesised that this tendency is more expressed in the high P/NI sub-sample since the larger gap between price and accounting numbers leaves more space for subjective valuations, which in turn bring out more of this optimism in analysts (*H3*).

In order for analysts to justify their optimism relative to high P/NI firms, it is expected that they will use a longer forecast horizon so that they can include a longer-term estimate of high earnings that justify the current high price relative to net income.

Finally, related to the rationale behind *H3* is the expectation that nonfinancial information is more referenced and consequently deemed more important in high P/NI firms (*H5*). This expectation is justified by the belief that the lack of share price justification from accounting numbers in this sub-sample will be compensated by nonfinancial-based justifications.

4.2 Sample Selection Process

Based on data of the largest non-financial firms listed on the London Stock Exchange, the sample selection process first started by choosing the fifteen highest and the fifteen lowest firms for the price to net income per share ratio, excluding those with negative net income.

Then only one analyst report per company was selected so that observations would be independent, as required by the Chi-Square test. The reports span from the 15th May till the 1st August 2014. They were selected based on the requirement of a minimum of 3 billable pages.

Furthermore, the reports were all retrieved from Investext via Thomson One Banker and required the existence of a price target in British pounds and a clear investment recommendation. The final prerequisite was that the report only covered one firm.

The final sample consisted on 30 analyst reports[30], one per firm, from 10 different brokers and averaging 15 pages per report. It is shown below:

[30] See list of firms and brokers in appendix (7.8).

Table 14 – Sample Separation Across High and Low P/NI

Low P/NI		High P/NI	
ICBSUC	Firm	ICBSUC	Firm
1757	FERREXPO PLC	2717	BAE SYSTEMS
1775	BHP BILLITON PLC	2737	DOMINO PRINTING
2727	VESUVIUS PLC	2791	RENTOKIL INITIAL PLC
2757	MELROSE INDUSTRIES	4573	BTG PLC
3577	UNILEVER PLC	533	TULLOW OIL PLC
533	AFREN PLC	5337	TESCO PLC
	ENQUEST PLC	5553	PERFORM GROUP LTD
	PREMIER OIL PLC	5759	TUI TRAVEL PLC
5337	J SAINSBURY PLC	6535	CABLE & WIRELESS
	WM. MORRISON SUPERMT	6575	VODAFONE GROUP PLC
537	BP PLC	7535	DRAX GROUP PLC
	ROYAL DUTCH SHELL	7577	PENNON GROUP PLC
5557	TALKTALK TELECOM	9537	SAGE GROUP PLC (THE)
573	PETROFAC LIMITED	9576	ARM HOLDINGS PLC
5755	CARNIVAL PLC		IMAGINATION TECH GRP

It can be seen that there is apparently little industry tendency to be high or low, since there are industries represented in both sides of the ratio: Oil Exploration and Production (533) and Specialised Consumer Services (5337). Moreover, it is noted that while the high P/NI sub-sample is more diverse in terms of industries represented, the low sub-sample has three industries which are represented by more than one firm.

4.3 Data Analysis

4.3.1 Dominant Valuation Models

As suggested by Demirakos *et al.* (2004), it is considered the dominant valuation model in an analyst's report either the one that is identified as basis for the target price or, when various models are used, the one closest to the target price. In this analysis, only dominant models will be scored since Demirakos *et al.* (2004) only found significance in their tests with dominant scoring.

The purpose of this analysis is to determine if there are differences in the use of valuation models from one sub-sample to another. Table 15 below shows the dominant valuation model per industry (henceforth identified with ICBSUC code) and per sub-sample.

As can be observed, both sub-samples rely mostly on flow-based models to reach their target price. The low P/NI sub-sample shows a higher dependence percentage, although in absolute terms the difference to the high sub-sample is of two analyst reports. In both sub-samples DCF is the most common valuation model, being that in the low sub-sample it represents 53% of dominant models used. In the high sub-sample this percentage goes down to little below 47%. This dominance within flow-based models would be even more clear if it were not for the specific cases of oil exploration and production (533) and biotechnology (4573) firms, which are valued with industry specific valuation models: the net asset valuation model (NAV) and the embedded value model (EmV)[31].

Table 15 – Analysis of Dominant Valuation Model in Analysts' Reports

Low P/NI	Firms	Flow-Based Valuation Models			Multiples-Based Valuation Models			
		DCF	EmV	NAV	P/E	EV/EBIT	EV/EBITDA	Hybrid Multiple
1757	1	1						
1775	1	1						
2727	1						1	
2757	1						1	
3577	1	1						
533	3			3 (100%)				
5337	2				2 (100%)			
537	2	2 (100%)						
5557	1	1						
573	1	1						
5755	1	1						
Distribution			73.33%				26.67%	

High P/NI	Firms	Flow-Based Valuation Models			Multiples-Based Valuation Models			
		DCF	EmV	NAV	P/E	EV/EBIT	EV/EBITDA	Hybrid Multiple
2717	1					1		
2737	1				1			
2791	1	1						
4573	1		1					
533	1			1				
5337	1	1						
5553	1	1						
5759	1	1						
6535	1	1						
6575	1						1	
7535	1	1						
7577	1							1
9537	1				1			
9576	2	1 (50%)			1 (50%)			
Distribution			60.00%				40.00%	

Additionally, it is visible that in the low sub-sample each industry tends to value firms with the same model, for those that are represented by more than one firm. Regarding the two industries represented in both sub-samples, due to the specific nature of oil exploration and production companies (533), NAV is consistently used in this industry either in the low or high P/NI sub-sample.

[31] See brief description in appendix (7.9).

Contrary to this case, in the consumer services industry (5337) firms with low P/NI were valued with a P/E multiple and one in the high sub-sample was valued with a DCF estimate. Since these three companies were analysed by three different brokers, the explanation may lie in the more common nature of the industry, where more than one model may be suitable.

Finally, in order to test the hypothesis laid out above, a Chi-Square test was performed to check if there were significant differences between each sub-sample's distribution of valuation models. With a p-value of 0.4386 the result is clear and rejects the premise that sub-samples have differences in regards to the use of valuation models.

4.3.2 Investment Recommendations

In order to analyse if there were any differences in the distribution of investment recommendations (buy, hold or sell) across sub-samples the following table (16) was designed. Contrary to expectations (*H3*), low P/NI firms have more buy recommendations. Despite being against one of the stated hypotheses it is understandable that this tendency occurs since these firms have a bottom line that more closely justifies their share price. Similarly, analysts show more caution regarding high P/NI firms but not a negative feeling, since the number of sell recommendations are the same.

Once again it should be stressed that within industries the recommendations are the same except in the case of semiconductors (9576). Furthermore, across sub-samples, the previous remark is also valid regarding 533 and 5337. This indicates that there is a strong industry-specific influence.

Finally, it is noted that recommendations are mostly optimistic, as found by Beckers *et al.* (2004). This implies a similarity across sub-samples that the chi-square test p-value of 0.6483 confirms by impeding a rejection of the null hypothesis that there is the same distribution of investment recommendations.

Table 16 – Analysis of Investment Recommendations in Analysts' Reports

Low P/NI	Firms	Investment Recommendation		
		Buy	Hold	Sell
1757	1	1		
1775	1	1		
2727	1	1		
2757	1	1		
3577	1	1		
533	3	3 (100%)		
5337	2			2 (100%)
537	2	2 (100%)		
5557	1	1		
573	1		1	
5755	1		1	
Distribution		73.33%	13.33%	13.33%

High P/NI	Firms	Investment Recommendation		
		Buy	Hold	Sell
2717	1		1	
2737	1		1	
2791	1	1		
4573	1	1		
533	1	1		
5337	1			1
5553	1	1		
5759	1	1		
6535	1		1	
6575	1	1		
7535	1	1		
7577	1	1		
9537	1			1
9576	2	1 (50%)	1 (50%)	
Distribution		60.00%	26.67%	13.33%

4.3.3 Forecast Horizons

With a similar purpose to the one in the previous sub-section, it is now intended to check analysts' reports to determine if the ratio P/NI is implies differences across sub-samples in what concerns forecast horizons.

Table 17 – Analysis of Forecast Horizons in Analysts' Reports

Low P/NI	Firms	Forecast Horizon (years ahead)				
		2	3	4	5	>5
1757	1					1
1775	1					1
2727	1	1				
2757	1		1			
3577	1		1			
533	3	1 (33.33%)	1 (33.33%)			1 (33.33%)
5337	2	1 (50%)		1 (50%)		
537	2		1 (50%)			1 (50%)
5557	1		1			
573	1					1
5755	1				1	
Distribution		20.00%	33.33%	6.67%	6.67%	33.33%

High P/NI	Firms	Forecast Horizon (years ahead)				
		2	3	4	5	>5
2717	1	1				
2737	1		1			
2791	1					1
4573	1					1
533	1		1			
5337	1		1			
5553	1		1			
5759	1			1		
6535	1				1	
6575	1					1
7535	1				1	
7577	1					1
9537	1		1			
9576	2	1 (50%)	1 (50%)			
Distribution		13.33%	40.00%	6.67%	13.33%	26.67%

The table above presents a similar distribution of forecast horizons for both sub-samples. For both most analysts (53.33%) forecasted a maximum of three years into the future. It is also curious to note that there are few observations outside of 3 or more than 5-years-ahead forecast horizons. This implies that a forecast horizon of either 3 or more than 5-years-ahead is the most common.

The results also show that this dispersion is industry independent since contrary to what has been verified so far not one industry has more than one analysis per forecast horizon. This only changes in one instance when we add the high P/NI 533 observation and get two firms in this industry for which estimates comprise three years.

Once again, the hypothesis of equal distributions between high and low P/NI observations is accepted since the commonly employed significance level of 5% is inferior to the p-value of 0.9469. Thus, we are unable to conclude that any differences occur.

4.4 Supplementary Analysis

4.4.1 Influence of Nonfinancial Information

Given that Trueman *et al.* (2000) found that nonfinancial information added increased explanatory power for share prices when added to net income, it is important to see if both analysts and companies regard this type of information as valuable or not.

In order to do so, analyst reports were screened for both unique references to nonfinancial information and dominant nonfinancial valuation justifications. This should reflect the overall influence of nonfinancial information over the analyst's recommendation.

Moreover, to see if companies recognise the importance of nonfinancial information, the key performance indicators (KPIs) listed in annual reports[32] were counted and separated into financial and nonfinancial.

4.4.1.1 Nonfinancial Information in Analyst Reports' First Page

The first page of an analyst report is the one that communicates more and more relevant information. There, analysts write down the information they deem most relevant and lay down their justifications for their investment recommendation. Having this in mind, only the first page of each report was studied as it contains the information that the analyst considered essential.

In a first stage, the number of unique nonfinancial and financial references included in the first page was counted. It was considered nonfinancial the reference to data that is not present in a firm's annual financial statements.

Then, the justifications[33] presented in the first page were counted as either financial or nonfinancial. A valuation justification designates in this dissertation each bullet point written by the analyst in the report's first page, excluding the descriptions of valuation methods used and their inputs. To determine if the justification was nonfinancial or financial, the text was analysed to see if its

[32] See list of annual reports used in appendix (7.10).
[33] See list of dominant financial and nonfinancial justifications in table 29 in appendix (7.11).

content discussed mostly nonfinancial or financial references, drawing a parallel with the rationale that determined a dominant valuation model used by Demirakos *et al.* (2004).

Table 18 – Analysis of Nonfinancial and Financial Information in Analysts' Reports

Low P/NI	Firms	Panel A: References		Panel B: Dominant Justifications	
		Nonfinancial	Financial	Nonfinancial	Financial
1757	1	3 (75%)	1 (25%)	2 (100%)	0 (0%)
1775	1	5 (71.43%)	2 (28.57%)	4 (100%)	0 (0%)
2727	1	3 (50%)	3 (50%)	3 (100%)	0 (0%)
2757	1	1 (33.33%)	2 (66.67%)	1 (33.33%)	2 (66.67%)
3577	1	1 (12.50%)	7 (87.50%)	1 (33.33%)	2 (66.67%)
533	3	9 (56.25%)	7 (43.75%)	6 (75%)	2 (25%)
5337	2	4 (40%)	6 (60%)	3 (60%)	2 (40%)
537	2	9 (40.91%)	13 (59.09%)	2 (50%)	2 (50%)
5557	1	6 (54.55%)	5 (45.45%)	1 (33.33%)	2 (66.67%)
573	1	0 (0%)	1 (100%)	0 (0%)	1 (100%)
5755	1	3 (37.50%)	5 (62.50%)	2 (40%	3 (60%)
Distribution		44 (45.83%)	52 (54.17%)	25 (60.98%)	16 (39.02%)
Sub-Sample Total		96 (55.17%)		41 (49.40%)	
High P/NI	Firms	Panel A: References		Panel B: Dominant Justifications	
		Nonfinancial	Financial	Nonfinancial	Financial
2717	1	0 (0%)	6 (100%)	0 (0%)	2 (100%)
2737	1	1 (16.67%)	5 (83.33%)	1 (33.33%)	2 (66.67%)
2791	1	1 (25%)	3 (75%)	1 (50%)	1 (50%)
4573	1	0 (0%)	3 (100%)	0 (0%)	2 (100%)
533	1	4 (80%)	1 (20%)	3 (100%)	0 (0%)
5337	1	3 (75%)	1 (25%)	2 (66.67%)	1 (33.33%)
5553	1	0 (0%)	3 (100%)	0 (0%)	3 (100%)
5759	1	7 (63.64%)	4 (36.36%)	3 (75%)	1 (25%)
6535	1	2 (33.33%)	4 (66.67%)	2 (66.67%)	1 (33.33%)
6575	1	3 (60%)	2 (40%)	3 (75%)	1 (25%)
7535	1	2 (66.67%)	1 (33.33%)	2 (66.67%)	1 (33.33%)
7577	1	3 (33.33%)	6 (66.67%)	1 (25%)	3 (75%)
9537	1	1 (33.33%)	2 (66.67%)	0 (0%)	2 (100%)
9576	2	5 (50%)	5 (50%)	2 (50%)	2 (50%)
Distribution		32 (41.03%)	46 (58.97%)	20 (47.62%)	22 (53.38%)
Sub-Sample Total		78 (44.83%)		42 (50.60%)	
Chi-Square Test P-Value		0.5249		0.2220	

Table 18 shows that analysts use more references when valuing low P/NI firms. This would at first glance be understandable since these firms are hypothesised in this dissertation as having a closer link with their accounting numbers. Thus it would be easier for analysts to refer to them. However, the key difference is in the number of nonfinancial references used, although there are also more financial references as well.

An important element to have in mind is that companies that explore and produce primary resources such as oil and metals have many (nonfinancial) references to production and external influences. This may explain the difference discussed above since the low sub-sample is rich in these industries: 533 and 537, for instance.

Looking at valuation justifications it is clear that there is more balance in the number used in low or high P/NI firms' reports. This is expected since most analysts used between 2 and 3 justifications in each report. However, it is noticeable that while the high P/NI sub-sample is more balanced in distribution of financial/nonfinancial justifications, low P/NI firms clearly tend to have more nonfinancial justifications. This is again explained by the previous paragraph.

Finally, both the distribution of references and justifications as nonfinancial or financial are accepted to be equal between the two sub-samples by the chi-square test p-value. Nonetheless, it should be stressed that with a lower p-value, there is more difference in the distribution of dominant justifications, having low P/NI firms more nonfinancial justifications than its sub-sample counterpart.

4.4.1.2 Nonfinancial Information in Annual Reports

Having analysed the analyst perspective on the influence of nonfinancial information over firm valuation, it is useful to compare it now to a firm-centric perspective. To that purpose, key performance indicators (KPIs) were analysed and split into financial and nonfinancial in the same fashion as references were above. KPIs were chosen because they are selected by each firm as representative of its performance, thus equating an analyst report's first page in the sense that it is the information deemed most relevant about the firm.

In this instance it is clear that low P/NI firms tend to include more financial measures, creating a perfectly balanced distribution of KPIs, whereas high P/NI firms present more nonfinancial indicators as representative of their performance. This is the inverse of what was seen with dominant valuation justifications in analyst reports, but is what was expected since the low sub-sample can more validly present to shareholders good financial indicators as representative of the firm's yearly performance. This is even more evident if the results are adjusted for the effect presented above and cause by the presence of two big oil companies (537) in the low sub-sample.

Moreover, the fact that the number of financial indicators is similar in both sub-samples, being the distribution of nonfinancial KPIs that tilts the balance, brings more credit to the rationale that high P/NI firms want to justify their performance with extra nonfinancial measures. This may happen because they feel that the traditional financial indicators are not enough to have a broad perspective of the firm's performance.

Table 19 – Analysis of Nonfinancial and Financial KPIs in Annual Reports[34]

Low P/NI	Firms	Key Performance Indicators (KPIs)	
		Nonfinancial	Financial
1757	1	6 (75%)	2 (25%)
1775	1	3 (37.50%)	5 (62.50%)
2727	1	3 (33.33%)	6 (66.67%)
2757	1	2 (28.57%)	5 (71.43%)
3577	1	6 (60%)	4 (40%)
533	3	15 (53.57%)	13 (46.43%)
5337	2	7 (30.43%)	16 (69.57%)
537	2	20 (71.43%)	8 (28.57%)
5557	1	4 (50%)	4 (50%)
573	1	3 (33.33%)	6 (66.67%)
Distribution		69 (50%)	69 (50%)
Sub-Sample Total		138 (47.42%)	

High P/NI	Firms	Key Performance Indicators (KPIs)	
		Nonfinancial	Financial
2717	1	4 (50%)	4 (50%)
2737	1	2 (28.57%)	5 (71.43%)
2791	1	9 (56.25%)	7 (43.75%)
4573	1	0 (0%)	4 (100%)
533	1	8 (88.89%)	1 (11.11%)
5337	1	11 (52.38%)	10 (47.62%)
5553	1	7 (77.78%)	2 (22.22%)
5759	1	6 (60%)	4 (40%)
6535	1	2 (40%)	3 (80%)
6575	1	7 (58.33%)	5 (41.67%)
7535	1	11 (91.67%)	1 (8.33%)
7577	1	10 (62.50%)	6 (37.50%)
9537	1	7 (53.85%)	6 (46.15%)
9576	1	6 (54.55%)	5 (45.45%)
Distribution		90 (58.82%)	63 (41.18%)
Sub-Sample Total		153 (52.58%)	
Chi-Square Test P-Value		0.1311	

Lastly, the chi-square test p-value shows is not low enough to reject the hypothesis of equal distribution of KPIs across sub-samples with the significance level of 5%. However, it is a remarkably low p-value that implies more differences in the abovementioned distribution than was detected in previous tests.

[34] Two firms in each sub-sample did not provide KPIs in their annual reports: Imagination Technologies Group (high P/NI, ICBSUC – 9586) and Carnival (low P/NI, ICBSUC – 5755).

4.4.2 Analyst Coverage

The number of analysts following firms in each sub-sample is also an object of study. Although not many conclusions are drawn from this study, it was revealed that the low sub-sample receives more coverage from brokers that its high counterpart. This may indicate that low P/NI firms are economically more relevant, but also that this sub-sample is easier to cover due to its closer ties to accounting numbers.

Table 20 – Analysis of Analyst Coverage

Low P/NI	Firms	Number of Analysts Covering (% Sub-Sample)
1757	1	19 (6.42%)
1775	1	27 (9.12%)
2727	1	12 (4.05%)
2757	1	11 (3.72%)
3577	1	18 (6.08%)
533	3	62 (20.95%)
5337	2	46 (15.54%)
537	2	45 (15.20%)
5557	1	16 (5.41%)
573	1	26 (8.78%)
5755	1	14 (4.73%)
Distribution		296 (53.05%)

High P/NI	Firms	Number of Analysts Covering (% Sub-Sample)
2717	1	18 (6.87%)
2737	1	8 (3.05%)
2791	1	17 (6.49%)
4573	1	9 (3.44%)
533	1	27 (10.31%)
5337	1	27 (10.31%)
5553	1	7 (2.67%)
5759	1	21 (8.02%)
6535	1	11 (4.20%)
6575	1	18 (6.87%)
7535	1	17 (6.49%)
7577	1	14 (5.34%)
9537	1	23 (8.78%)
9576	2	45 (17.18%)
Distribution		262 (46.95%)

4.4.3 Firm Size

In order to complement what was deduced above regarding firm economic relevancy, firm size was also approached. Firm size is measured here by firm market capitalisation at 31/12/2013.

Table 21 – Analysis of Firm Size

Low P/NI	Firms	Firm Size Measured by Market Capitalisation				
		Mega (>$100 Billion)	Large (>$10 Billion)	Mid-Size (>$2 Billion)	Small (>$300 Million)	Micro (<$300 Million)
1757	1				1	
1775	1		1			
2727	1				1	
2757	1			1		
3577	1		1			
533	3				3 (100%)	
5337	2			2 (100%)		
537	2	1 (50%)	1 (50%)			
5557	1			1		
573	1			1		
5755	1			1		
Distribution		6.67%	20.00%	40.00%	33.33%	0.00%

High P/NI	Firms	Firm Size Measured by Market Capitalisation				
		Mega (>$100 Billion)	Large (>$10 Billion)	Mid-Size (>$2 Billion)	Small (>$300 Million)	Micro (<$300 Million)
2717	1		1			
2737	1				1	
2791	1			1		
4573	1			1		
533	1			1		
5337	1		1			
5553	1				1	
5759	1			1		
6535	1				1	
6575	1	1				
7535	1			1		
7577	1			1		
9537	1			1		
9576	2		1 (50%)		1 (50%)	
Distribution		6.67%	20.00%	46.67%	26.67%	0.00%

It results from the analysis that the distribution of firm size by low or high P/NI is essentially the same. A chi-square test p-value of 0.9959 clearly accepts that fact, resulting from this that the P/NI ratio has no implications over firm size as measured by market capitalisation.

4.5 Concluding Remarks on the Small Sample Analysis

In general, the small sample analysis concluded that the separation of a sample between according to P/NI is not significant, leading only to slight differences in the distributions of analysed variables and to no rejections of the hypotheses of such distributions being equal between the two sub-samples by chi-square tests.

It was found that flows-based valuation models were more common in both sub-samples, contrary to what Demirakos *et al.* (2004) found. This is consistent with the fact that the flow-based model used in the large sample (RIM) had a higher explanatory power of market prices. Within each type of model, the most common were DCF and P/E and price to cash flow was not used, consistent with the findings of Demirakos *et al.* (2004). In fact the DCF was the most common model overall, which is consistent with Penman (2001). However, this rejects *H1* as had been defined previously:

- ***H1:*** *Multiple-based valuation is the most common method used by analysts*

Ultimately, this also leads to the rejection of *H2* since for the high sub-sample flows-based valuation is the most common, but it is noted that multiples-based valuation increases. This is in line with the rationale presented for *H2*, whereby the value of high P/NI firms is better reflected by multiples since this method best mirrors value according to market and not to accounting numbers. Furthermore, it was also found in the large sample analysis that the P/E multiple was unbiased for high P/OI observations. This supports the use of this multiple on firms which market price is less close to income-based performance. Likewise, the P/E multiple is the most used, which confirms the findings of Demirakos *et al.* (2004).

- ***H2:*** *H1 is even more evident in high P/NI firms*

Regarding investment recommendations, findings were consistent with the optimism revealed by Beckers *et al.* (2004). However, contrary to expectations, there is more optimism – more buy recommendations – for the low sub-sample. Adding to this the fact that the number of sell recommendations was the same, it can be assumed that analysts are more cautious towards high P/NI firms, rather than pessimistic. Again this finding is consistent with the large sample in the sense that low P/OI firms had a higher mean overvaluation. The optimism towards low P/NI is easily explained by the fact that these firms have a higher net income to justify their share price. Thus, *H3* is rejected.

- ***H3:*** *Analysts are more optimistic, i.e. have more buy recommendations, with high Price to Net Income firms*

Similarly, *H4* is also rejected as it was found that there was a very similar distribution of forecast horizons between both sub-samples. This is confirmed by the high p-value of 0.9469 that clearly accepts the equality of the two distributions.

- ***H4:*** *Analysts use a longer forecast horizon for high P/NI firms*

Regarding the use nonfinancial information there were mixed results. On one hand, analysts refer more to nonfinancial data and justify valuation more often with nonfinancial explanations. On the other hand, the firms' perspective shows otherwise since while low P/NI firms have the same number of financial and nonfinancial KPIs, the high sub-sample clearly tends towards more of the latter. These two different perspectives and the inconclusive results of the chi-square tests do not allow a validation of *H5*.

- ***H5:*** *Nonfinancial information is more useful for high P/NI firms*

Finally, the research question cannot be answered affirmatively because although slight differences were observed and commented on, the test results were not significant in detecting any differences.

- ***Research Question:*** *Is analyst treatment of high Price to Net Income (P/NI) firms different from their treatment of low P/NI companies?*

Chapter 5: Conclusion

Surprisingly, in the large sample analysis valuation models were found to be more accurate and less biased when applied to high P/OI. A possible explanation is that analysts are more cautious in predicting future earnings for firms that have a bigger gap between share price and operational performance, as was visible with the lower mean mdfy1 and mdfy2 for A_H. This cautious attitude was also found in the small sample, with analysts having the same number of sell recommendations but more hold vs. buy indications.

While in the large sample P/OI proved to be a significant ratio in sample separation, with tests rejecting the equality of mean and median valuation errors between high and low sub-samples, in the small sample results were not significant. Naturally this is also due to the nature of the small sample, which has less statistical power, but it shows that P/OI can be more relevant a ratio than P/NI. This is natural considering that true operational performance is a more distinctive figure than net income, which can include several non-firm-specific or extraordinary elements.

Although no significant differences in the treatment of high vs. low P/NI firms by analysts were found, interesting observations were made in the small sample analysis. Nonfinancial information was found to be more important for analysts when used to justify low P/NI firms, whereas it was more relevant for high P/NI firms to include in key performance indicators. This leads to the possibility that despite the fact that high P/NI firms consider themselves to be better represented by nonfinancial data, analysts refrain from using it with these firms due to their cautious attitude towards high price to performance firms. On the other hand, since the low sub-sample has a net income more closely related to share price, analysts may rely more on nonfinancial information, and consequently be less cautious, due to sensing a higher degree of solidity in accounting numbers.

It should be stressed that the choice of different ratios to separate the large and small samples compromised coherence between the two analyses, consisting in a major caveat. Nonetheless, consistency was found and noted in both chapters' results. Moreover, it was important in order to verify that P/OI is a more distinctive feature than P/NI.

Thus, it would be interesting for further research with a coherent separation of small sample by P/OI in order to detect if significant differences would be found then. Furthermore, since remarkable intra-industry consistency was found in the small sample, it would be an improved study the one that had the same number of firms per industry in each sub-sample of the small sample in order to eliminate the industry-specific effect and isolate the ratio's effect.

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7. Appendices

7.1 Definition of Variables Used in the Large Sample Analysis

Table 22 – Definition of All Variables

Variable	Database	Type	Units	Description
ABSERROR_PE	N/A	Num	% of P4	Absolute Error of P/E Valuation Relative to P4
ACT	Compustat	Num	$ Millions	Total Current Assets
ACTUAL	I/B/E/S	Num	$ Millions	IBES Actual Earnings
AE_VAL_RIVM	N/A	Num	% of P4	Absolute Error of RIM Valuation Relative to P4
AJEX	Compustat	Num	N/A	Adjustment Factor
AM	Compustat	Num	$ Millions	Amortization of Intangibles
AQC	Compustat	Num	$ Millions	Acquisitions
AT	Compustat	Num	$ Millions	Total Assets
BETA	CRSP	Num	N/A	Market Beta Using Daily Returns
BPS	N/A	Num	$	Total Common Equity per Share (Adjusted with AJEX)
BPS1	N/A	Num	$	$BPS + MDFY1 \times (1 - \frac{DVC}{EPS})$ (24)
CAPX	Compustat	Num	$ Millions	Capital Expenditures
CEQ	Compustat	Num	$ Millions	Total Common Equity
CHE	Compustat	Num	$ Millions	Cash and Short-Term Investments
CONM	Compustat	Char	N/A	Company Name
CSHO	Compustat	Num	Millions	Common Shares Outstanding
CSHPRI	Compustat	Num	Millions	Common Shares Used to Calculate Earnings Per Share - Basic
CV	N/A	Num	$	$\frac{RI2/(KE-G)}{1+KE}$ (25)
DATADATE		Num	N/A	Fiscal Year End Date
DIFF_AE	N/A	Num	%	Difference in Absolute Errors Between the RIM and P/E multiple
DC_RI1	N/A	Num	$	Discounted RI1 at Cost of Equity Capital
DD1	Compustat	Num	$ Millions	Long-Term Debt Due in One Year
DLC	Compustat	Num	$ Millions	Total Debt in Current Liabilities
DLTT	Compustat	Num	$ Millions	Total Long-Term Debt

DP	Compustat	Num	$ Millions	Depreciation and Amortization	
DPAYOUT	N/A	Num	$	DVC/EPS	*(26)*
DPC	Compustat	Num	$ Millions	Depreciation and Amortization (Cash Flow)	
DVC	Compustat	Num	$ Millions	Dividends Common	
DVPA	Compustat	Num	$ Millions	Preferred Dividends in Arrears	
EP	N/A	Num	$	$MDFY2/P4$	*(27)*
EPS	N/A	Num	$	EPSPX Adjusted with AJEX	
EPSPX	Compustat	Num	$ Millions	Earnings Per Share Excluding Extraordinary Items	
FYEAR	Compustat	Num	N/A	Fiscal Year	
G	N/A	Num	%	Assumed Growth Rate for RIM	
GVKEY	Compustat	Char	N/A	Global Company Key	
HIGH	N/A	Num	N/A	Dummy that Equals 1 (0) if Observation is High (Low) P/OI	
HMEAN_PE	N/A	Num	$	Harmonic Mean of Yearly, SIC3 Comparables' P/E	
IB	Compustat	Num	$ Millions	Income Before Extraordinary Items	
INTAN	Compustat	Num	$ Millions	Total Intangible Assets	
INVT	Compustat	Num	$ Millions	Total Inventories	
IVCH	Compustat	Num	$ Millions	Increase in Investments	
KE	N/A	Num	N/A	Cost of Equity Capital (r_e, *20*)	
LCT	Compustat	Num	$ Millions	Total Current Liabilities	
MDFY1	I/B/E/S	Num	$	Median of 1-Year-Ahead EPS Forecasts	
MDFY2	I/B/E/S	Num	$	Median of 2-Year-Ahead EPS Forecasts	
MDFY3	I/B/E/S	Num	$	Median of 3-Year-Ahead EPS Forecasts	
MDFY4	I/B/E/S	Num	$	Median of 4-Year-Ahead EPS Forecasts	
MDFY5	I/B/E/S	Num	$	Median of 5-Year-Ahead EPS Forecasts	
MDLTG	I/B/E/S	Num	$	Median of Long-Term Growth Forecasts	
MNFY1	I/B/E/S	Num	$	Mean of 1-Year-Ahead EPS Forecasts	
MNFY2	I/B/E/S	Num	$	Mean of 2-Year-Ahead EPS Forecasts	
MNFY3	I/B/E/S	Num	$	Mean of 3-Year-Ahead EPS Forecasts	
MNFY4	I/B/E/S	Num	$	Mean of 4-Year-Ahead EPS Forecasts	

MNFY5	I/B/E/S	Num	$	Mean of 5-Year-Ahead EPS Forecasts
MNLTG	I/B/E/S	Num	$	Mean of Long-Term Growth Forecasts
NI	Compustat	Num	$ Millions	Net Income (Loss)
NUFY1	I/B/E/S	Num	N/A	Number of 1-Year-Ahead EPS Forecasts
NUFY2	I/B/E/S	Num	N/A	Number of 2-Year-Ahead EPS Forecasts
NUFY3	I/B/E/S	Num	N/A	Number of 3-Year-Ahead EPS Forecasts
NUFY4	I/B/E/S	Num	N/A	Number of 4-Year-Ahead EPS Forecasts
NUFY5	I/B/E/S	Num	N/A	Number of 5-Year-Ahead EPS Forecasts
NULTG	I/B/E/S	Num	N/A	Number of Long-Term Growth Forecasts
OANCF	Compustat	Num	$ Millions	Net Cash Flow from Operating Activities
OIADP	Compustat	Num	$ Millions	Operating Income After Depreciation
OIBDP	Compustat	Num	$ Millions	Operating Income Before Depreciation
P4	I/B/E/S	Num	$	Share Price in April
PE	N/A	Num	$	$P4/MDFY2$ *(28)*
PERMNO	CRSP	Num	N/A	Permanent Identification Number in CRSP
PPENT	Compustat	Num	$ Millions	Total (Net) Property, Plant, and Equipment
PRCC_C	Compustat	Num	$	Annual (Calendar) Price Close
PRCC_F	Compustat	Num	$	Annual (Fiscal) Price Close
PRICETOOI	N/A	Num	$	$P/OI = P4/\left(\frac{OIBDP}{CSHPRI \times AJEX}\right)$ *(29)*
PSTK	Compustat	Num	$ Millions	Total Preferred Stock
PSTKL	Compustat	Num	$ Millions	Preferred Stock – Liquidating Value
RECT	Compustat	Num	$ Millions	Total Receivables
RI1	N/A	Num	$	$MDFY1 - KE \times BPS$ *(30)*
RI2	N/A	Num	$	$MDFY2 - KE \times BPS1$ *(31)*
SALE	Compustat	Num	$ Millions	Sales
SE_VAL_RIVM	N/A	Num	% of P4	Signed Error of RIM Valuation Relative to P4
SERROR_PE	N/A	Num	% of P4	Signed Error of P/E Valuation Relative to P4
SIC2	Compustat	Num	N/A	2-Digit SIC
SIC3	Compustat	Num	N/A	3-Digit SIC

SICH	Compustat	Num	N/A	Standard Industrial Classification – Historical
SIV	Compustat	Num	$ Millions	Sale of Investments
SPI	Compustat	Num	$ Millions	Special Items
SPPE	Compustat	Num	$ Millions	Sale of Property
TIC	Compustat	Char	N/A	Ticker Symbol
TICKER	I/B/E/S	Char	N/A	I/B/E/S Company Identifier
TSTKP	Compustat	Num	$ Millions	Preferred Treasury Stock
TXT	Compustat	Num	$ Millions	Total Income Taxes
V_HMEAN_PE	N/A	Num	$	P/E Valuation *(3)* using Harmonic Mean *(8)*
VAL_RIVM	N/A	Num	$	RIM Valuation *(18)*
VALDATE		Num	N/A	Valuation Date
XIDO	Compustat	Num	$ Millions	Extraordinary Items and Discontinued Operations
XINT	Compustat	Num	$ Millions	Total Interest and Related Expense
XRD	Compustat	Num	$ Millions	Research and Development Expense

7.2 Large Sample Analysis – Sample B Descriptive Statistics

Table 23 - Sample B Descriptive Statistics

Panel A: Pooled Sample B	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	5263	30.1769	19.9570	25.7900	2.7800	15.2100	40.3300	132.6000
Common Equity per Share (BPS)	5263	12.7892	8.9095	10.6262	0.6791	6.0887	17.3554	54.8257
EPS Excl. Extraordinary Items (EPS)	5263	1.6969	1.4105	1.3300	0.0350	0.6800	2.2900	10.2300
Price to OIBDP (P/OI)	5263	10.0788	8.3102	7.8107	1.5111	5.2594	11.7868	73.5345
Median 1-Year-Ahead EPS (MDFY1)	5263	1.8560	1.3367	1.5200	0.0100	0.8500	2.5300	8.4100
Median 2-Year-Ahead EPS (MDFY2)	5263	2.1592	1.4582	1.8000	0.1500	1.0500	2.9000	8.1800

Panel B: Sub-Sample B_L	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2633	27.5723	17.3466	24.0700	2.8200	14.7600	37.0100	112.8600
Common Equity per Share (BPS)	2633	15.1702	9.5588	13.2442	0.8591	7.8814	20.4644	54.8257
EPS Excl. Extraordinary Items (EPS)	2633	2.0055	1.5512	1.6283	0.0350	0.8900	2.6900	10.2300
Price to OIBDP (P/OI)	2633	5.2609	1.7883	5.2596	1.5111	3.8714	6.6677	9.5715
Median 1-Year-Ahead EPS (MDFY1)	2633	2.0323	1.3926	1.7000	0.0100	0.9900	2.7200	8.4100
Median 2-Year-Ahead EPS (MDFY2)	2633	2.3052	1.4776	1.9700	0.1800	1.2000	3.0400	8.1800

Panel C: Sub-Sample B_H	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2630	32.7844	21.9619	27.2750	2.7800	16.0500	44.6000	132.6000
Common Equity per Share (BPS)	2630	10.4055	7.4862	8.5009	0.6791	4.9824	13.6270	50.4788
EPS Excl. Extraordinary Items (EPS)	2630	1.3881	1.1756	1.0500	0.0400	0.5200	1.9100	9.3800
Price to OIBDP (P/OI)	2630	14.9022	9.4075	11.7877	5.3692	9.4351	16.7245	73.5345
Median 1-Year-Ahead EPS (MDFY1)	2630	1.6796	1.2540	1.3300	0.0200	0.7300	2.3300	6.6600
Median 2-Year-Ahead EPS (MDFY2)	2630	2.0131	1.4239	1.6300	0.1500	0.9400	2.7500	7.5600

7.3 Large Sample Analysis – Sample C Descriptive Statistics

Table 24 - Sample C Descriptive Statistics

Panel A: Pooled Sample C	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	5198	30.2136	20.0038	25.8500	2.7800	15.2000	40.3300	132.6000
Common Equity per Share (BPS)	5198	12.7967	8.9032	10.6519	0.6791	6.1014	17.3667	54.8257
EPS Excl. Extraordinary Items (EPS)	5198	1.6971	1.4104	1.3300	0.0350	0.6800	2.2900	10.2300
Price to OIBDP (P/OI)	5198	10.0970	8.3446	7.8127	1.5111	5.2596	11.7953	73.5345
Median 1-Year-Ahead EPS (MDFY1)	5198	1.8578	1.3378	1.5200	0.0100	0.8500	2.5300	8.4100
Median 2-Year-Ahead EPS (MDFY2)	5198	2.1610	1.4598	1.8000	0.1500	1.0500	2.9000	8.1800

Panel B: Sub-Sample C_L	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2625	25.4851	17.0141	21.5900	2.7800	13.1900	33.7600	127.5400
Common Equity per Share (BPS)	2625	13.6964	9.1571	11.5830	0.8591	6.8976	18.6520	54.8257
EPS Excl. Extraordinary Items (EPS)	2625	1.8524	1.5234	1.4500	0.0350	0.7700	2.5000	10.2300
Price to OIBDP (P/OI)	2625	5.9554	2.6737	5.5357	1.5111	3.8917	7.4739	16.5241
Median 1-Year-Ahead EPS (MDFY1)	2625	1.8840	1.3618	1.5400	0.0100	0.8900	2.5200	8.4100
Median 2-Year-Ahead EPS (MDFY2)	2625	2.1486	1.4533	1.8000	0.1800	1.0800	2.8500	8.1800

Panel C: Sub-Sample C_H	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
Share Price in April (P4)	2573	35.0376	21.6129	30.6700	2.9100	18.5500	46.4400	132.6000
Common Equity per Share (BPS)	2573	11.8788	8.5411	9.6006	0.6791	5.4746	16.0310	51.1398
EPS Excl. Extraordinary Items (EPS)	2573	1.5387	1.2658	1.2200	0.0400	0.5900	2.1600	9.3800
Price to OIBDP (P/OI)	2573	14.3222	9.9016	11.2833	2.6230	8.1635	16.8741	73.5345
Median 1-Year-Ahead EPS (MDFY1)	2573	1.8311	1.3125	1.5000	0.0400	0.8100	2.5500	7.6100
Median 2-Year-Ahead EPS (MDFY2)	2573	2.1735	1.4666	1.8200	0.1500	1.0300	2.9700	8.0100

7.4 Large Sample Analysis – Sample A Descriptive Statistics by SIC3

Table 25 - Sample A Descriptive Statistics by SIC3

Pooled Sample A	**Mean**						**Median**					
3-Digit SIC	**P4**	**BPS**	**EPS**	**P/OI**	**MDFY1**	**MDFY2**	**P4**	**BPS**	**EPS**	**P/OI**	**MDFY1**	**MDFY2**
104	28.8	15.0	1.4	14.4	1.9	2.4	29.4	20.8	1.0	10.5	1.5	2.4
122	37.5	10.1	1.7	8.3	2.3	3.2	36.8	9.5	1.5	8.1	2.4	3.1
131	35.9	16.2	2.1	7.6	2.1	2.5	31.0	13.7	1.5	5.6	1.6	2.1
138	27.4	14.2	2.2	5.9	2.3	2.8	25.7	12.3	1.8	5.4	2.0	2.5
140	52.8	17.5	2.4	9.8	2.6	3.3	36.0	13.1	1.9	9.2	2.1	2.4
153	33.4	31.6	4.5	6.3	1.2	1.7	30.8	31.4	3.8	4.8	1.0	1.5
160	32.7	11.9	2.0	8.2	2.0	2.3	30.5	12.1	1.8	6.6	1.8	2.4
162	18.8	10.4	1.1	8.8	1.2	1.5	16.6	10.6	0.9	7.6	1.2	1.4
170	12.6	7.3	1.1	8.1	0.9	1.3	13.1	6.1	0.7	8.9	0.9	1.1
202	13.9	6.5	0.7	13.3	1.0	1.3	13.4	7.9	0.7	10.7	1.1	1.2
204	54.2	16.1	3.6	7.1	4.0	4.4	54.2	15.9	3.4	7.5	3.8	4.1
205	16.9	6.2	0.7	8.6	0.8	1.0	17.1	5.8	0.7	8.8	0.8	1.0
206	42.5	7.3	1.5	13.5	1.8	2.0	44.9	9.1	1.5	14.2	2.0	2.2
207	10.3	6.6	0.9	6.1	0.9	1.1	9.3	7.5	0.8	6.4	0.8	1.2
208	41.5	12.7	2.3	10.0	2.5	2.7	35.8	10.7	2.2	10.6	2.3	2.6
209	21.3	6.4	0.7	10.4	0.9	1.1	19.4	5.2	0.6	9.8	0.8	1.1
211	32.7	6.8	2.4	7.5	2.4	2.6	28.9	3.7	2.2	7.9	2.2	2.4
227	28.2	18.2	1.4	6.3	1.7	2.1	14.1	5.0	0.6	6.7	0.9	1.2
230	36.5	14.7	2.0	10.8	2.2	2.6	30.9	10.0	1.8	8.8	1.8	2.3
233	31.6	13.1	1.9	7.5	2.0	2.2	31.6	13.1	1.9	7.5	2.0	2.2
240	21.4	9.3	1.6	10.4	0.6	1.0	20.9	8.6	0.6	11.8	0.7	1.0
242	38.5	17.2	1.0	16.5	0.8	1.2	39.6	17.3	0.8	11.5	0.8	0.9
245	13.6	5.7	1.9	7.0	0.7	1.1	13.6	5.7	1.9	7.0	0.7	1.1
251	22.5	7.4	1.0	9.2	1.2	1.4	21.9	9.6	1.1	9.1	1.0	1.4
262	27.5	12.2	2.1	5.1	2.1	2.4	18.8	11.3	1.8	5.1	1.4	1.9
263	27.0	14.1	2.3	5.4	1.7	2.0	27.7	15.2	1.7	5.4	1.6	2.0
265	29.9	7.8	1.2	8.9	1.4	1.6	25.3	6.6	1.2	7.8	1.5	1.6
267	37.6	13.8	2.4	6.7	2.6	2.9	30.3	15.1	1.7	6.4	1.8	2.4
271	23.7	18.9	2.0	4.9	1.8	2.0	19.3	9.8	1.8	4.3	1.5	2.0
275	22.4	10.3	1.0	7.0	1.4	1.6	16.5	9.5	1.0	6.2	1.3	1.4
278	32.7	7.1	1.6	5.9	2.3	2.6	24.8	7.1	1.9	6.9	2.5	2.8
280	32.1	12.9	1.5	6.1	2.1	2.5	31.8	14.2	1.5	6.1	2.1	2.4
281	34.1	12.1	2.0	8.2	2.2	2.5	29.1	12.5	1.7	7.6	1.9	2.1
282	29.2	10.2	1.9	6.8	2.2	2.5	27.4	9.9	1.9	6.4	2.2	2.5
283	35.2	10.2	1.7	13.6	2.3	2.5	33.6	9.4	1.5	10.5	2.1	2.4
284	39.2	7.7	2.0	9.3	2.2	2.5	35.9	6.7	1.7	9.7	2.0	2.2
285	59.3	15.9	3.2	7.0	3.9	4.4	65.5	14.8	4.2	6.6	4.5	5.0
286	33.6	11.7	2.1	6.4	2.4	2.8	32.0	10.1	2.2	6.8	2.6	2.8
287	29.1	8.6	2.0	9.1	2.2	2.3	17.0	5.3	0.7	9.7	0.9	1.2

289	39.2	14.9	2.2	7.4	2.5	3.0	40.2	12.3	2.0	7.2	2.1	2.5
291	40.2	21.5	4.0	5.9	3.9	4.3	35.1	22.5	3.8	4.5	3.6	3.9
301	50.5	29.5	1.9	11.2	2.9	2.8	50.5	29.5	1.9	11.2	2.9	2.8
308	29.9	13.6	1.7	7.4	2.0	2.3	31.5	12.4	1.6	7.3	1.9	2.1
314	22.4	10.9	1.3	9.1	1.4	1.7	20.3	10.7	1.2	9.1	1.3	1.6
329	41.2	21.8	2.6	8.9	2.4	2.8	33.9	22.3	2.3	7.1	2.3	2.8
331	32.2	16.6	2.1	7.1	2.2	2.8	29.2	18.1	2.0	6.4	1.9	2.7
334	19.1	23.0	1.6	6.8	1.4	1.9	20.1	23.4	0.9	5.4	0.9	1.6
335	30.0	17.6	1.8	8.0	2.0	2.4	29.6	15.9	1.6	7.0	1.9	2.4
339	25.0	10.5	1.1	11.4	1.1	2.4	25.0	10.5	1.1	11.4	1.1	2.4
341	31.2	7.3	2.0	5.7	2.2	2.4	26.7	7.3	1.8	5.5	2.1	2.2
342	34.1	17.0	1.9	7.9	2.3	2.8	29.5	15.6	1.4	7.5	1.5	1.8
344	41.5	16.8	2.0	8.3	2.2	2.7	28.0	15.3	1.5	7.9	1.7	2.0
348	13.6	5.0	1.4	4.9	0.8	0.9	13.6	5.0	1.4	4.9	0.8	0.9
349	35.5	18.5	1.8	10.5	2.2	2.6	33.8	20.7	1.7	8.2	2.2	2.6
351	40.8	10.7	1.6	12.0	2.2	3.0	47.7	11.6	1.5	12.6	2.0	3.0
353	41.8	15.9	2.4	9.8	2.6	3.1	36.7	14.4	2.2	9.6	2.4	2.8
354	42.5	16.5	3.7	6.9	3.0	3.4	34.2	16.8	3.0	6.4	2.4	2.7
355	26.7	12.5	1.8	12.7	1.7	2.0	24.9	12.7	1.3	9.9	1.4	1.8
356	32.1	12.7	1.7	11.0	2.0	2.3	32.3	13.1	1.5	9.6	1.7	2.1
357	22.1	8.9	0.9	17.1	1.3	1.5	19.1	7.4	0.6	12.0	0.9	1.2
358	38.7	10.0	2.0	9.3	2.3	2.7	38.2	10.7	1.9	9.7	2.3	2.8
361	63.6	30.8	2.6	9.3	3.9	4.7	64.3	30.6	3.3	8.6	4.0	4.5
362	30.6	14.2	1.9	9.2	2.3	2.7	23.8	10.6	1.5	7.4	2.1	2.5
364	43.2	17.7	2.9	8.6	2.8	3.2	43.0	17.9	2.7	9.0	3.0	3.3
366	23.1	11.0	1.3	13.1	1.4	1.6	16.8	7.0	0.7	11.7	0.9	1.1
367	20.4	7.9	1.0	15.8	1.2	1.4	16.4	7.4	0.8	11.9	1.0	1.3
369	19.6	11.1	1.2	8.4	1.5	1.7	17.8	10.3	0.8	6.1	1.3	1.5
371	26.3	12.3	1.8	8.8	1.8	2.2	19.9	9.9	0.9	7.2	1.1	1.5
372	42.5	15.0	2.6	7.6	2.9	3.4	35.9	13.9	2.2	7.7	2.5	2.9
373	37.8	16.8	2.3	9.0	2.4	2.7	23.2	21.1	1.8	10.1	1.4	1.8
374	34.5	15.2	2.0	10.7	2.0	2.3	31.6	16.2	1.8	9.2	1.9	2.4
379	36.9	12.2	2.9	6.6	3.1	3.4	25.7	4.8	1.7	5.8	1.8	2.0
381	41.5	20.9	3.0	14.9	3.1	3.5	37.8	18.5	2.1	9.8	2.4	2.8
382	35.4	13.1	1.5	14.9	1.9	2.2	28.0	10.7	1.1	12.3	1.4	1.7
384	32.2	12.0	1.4	14.4	1.7	1.9	27.3	10.4	1.1	11.4	1.3	1.6
386	5.2	3.5	0.4	6.1	0.5	0.6	5.2	3.5	0.4	6.1	0.5	0.6
394	19.5	9.7	1.4	8.5	1.4	1.6	18.4	8.8	1.4	7.5	1.4	1.6
399	20.5	7.9	1.0	11.0	1.0	1.3	15.1	5.9	1.0	8.0	0.7	1.0
401	47.1	21.1	2.8	7.0	2.9	3.4	44.8	22.5	2.5	7.2	2.7	3.2
421	27.3	9.7	1.3	7.4	1.4	1.7	20.5	9.2	1.1	6.8	1.0	1.4
440	40.6	23.6	2.7	6.7	2.4	2.9	39.1	25.5	2.4	6.7	2.5	2.6
441	41.2	31.5	4.6	6.0	4.2	4.5	37.8	31.8	4.4	6.0	4.5	4.3
451	20.8	10.4	1.7	5.2	2.0	2.3	15.7	8.9	1.7	3.4	1.4	1.7
470	32.8	18.0	2.0	7.5	2.1	2.4	36.3	20.9	1.9	6.5	2.3	2.5
473	33.3	8.1	1.3	13.1	1.5	1.8	31.9	7.8	1.5	13.2	1.6	1.8

481	28.6	14.3	1.6	5.6	1.5	1.8	23.4	9.7	1.4	4.0	1.2	1.4
483	22.2	10.9	1.3	7.1	1.3	1.5	20.9	9.2	1.0	6.3	1.1	1.3
484	34.4	15.0	2.2	7.4	2.1	2.5	27.8	14.8	1.3	5.0	1.6	2.1
488	19.8	15.6	1.0	5.5	1.4	1.6	20.0	13.9	0.8	6.0	1.3	1.5
489	26.2	10.4	0.9	8.4	1.1	1.4	22.5	8.3	0.8	6.7	1.0	1.2
491	34.9	22.4	2.3	5.0	2.4	2.6	32.2	19.6	2.2	4.5	2.3	2.4
492	35.1	16.8	2.1	6.0	2.1	2.3	32.3	17.6	2.0	5.4	2.1	2.3
493	34.4	23.2	2.3	4.8	2.4	2.6	30.9	21.8	2.1	4.7	2.4	2.5
494	22.5	11.8	1.0	7.6	1.1	1.2	20.5	11.2	0.9	7.6	1.0	1.1
495	31.0	10.1	1.3	8.9	1.4	1.7	28.0	10.0	1.2	7.5	1.4	1.6
499	14.0	6.9	0.6	10.0	0.7	0.8	14.0	7.2	0.7	5.8	0.6	0.7
501	29.8	10.9	1.5	8.4	1.9	2.1	17.0	9.5	0.7	9.8	1.2	1.4
504	31.0	15.6	1.8	9.2	2.0	2.3	29.2	16.0	1.7	7.8	1.9	2.2
505	34.5	21.9	2.7	6.5	3.0	3.4	31.6	24.0	2.5	5.9	2.7	3.1
506	33.4	16.5	2.8	7.5	2.9	3.2	31.7	16.4	2.6	7.2	2.9	3.0
507	29.7	13.9	1.7	7.2	2.0	2.4	21.1	13.4	1.5	6.4	2.0	2.6
508	24.2	10.1	1.4	6.9	1.8	2.1	23.5	10.4	1.4	7.4	1.8	2.0
509	19.6	5.1	0.9	8.7	1.2	1.5	18.1	5.5	1.0	8.6	1.1	1.6
512	22.8	9.5	1.1	8.1	1.5	1.7	19.2	11.1	1.3	7.3	1.5	1.6
517	36.0	16.5	2.3	9.6	2.2	2.6	30.6	18.7	2.0	9.8	2.0	2.2
550	21.1	15.4	1.6	5.2	1.7	2.0	19.2	12.5	1.5	4.7	1.6	1.8
581	31.3	8.9	1.4	8.5	1.6	1.8	26.6	7.8	1.1	7.9	1.3	1.5
591	34.8	20.0	1.8	7.5	2.4	2.8	36.4	22.9	1.8	6.7	2.6	2.9
594	24.7	8.5	1.1	12.4	1.2	1.5	22.2	8.0	1.0	7.1	1.1	1.3
596	18.2	7.7	0.9	10.3	1.0	1.2	14.1	7.4	0.9	7.0	0.9	1.1
701	31.9	9.9	1.9	8.7	1.2	1.6	32.1	9.6	1.8	8.7	1.2	1.6
720	10.1	6.3	0.4	4.8	0.5	0.6	10.1	6.2	0.4	4.6	0.5	0.6
731	25.1	8.8	1.6	9.3	1.6	1.9	24.9	9.7	1.0	7.8	1.3	1.5
732	31.0	11.4	1.9	7.3	2.2	2.5	35.8	11.7	2.0	7.6	2.5	2.7
733	34.6	20.6	1.7	8.8	1.7	2.0	32.2	21.1	1.5	9.8	1.5	1.7
734	11.9	2.0	0.4	17.3	0.5	0.5	11.9	2.0	0.4	17.3	0.5	0.5
735	25.4	13.0	1.9	3.9	2.1	2.4	23.9	11.9	1.7	3.4	1.8	2.0
736	19.9	10.4	1.1	10.2	1.1	1.3	16.7	8.1	0.8	9.3	0.9	1.1
737	24.4	7.4	0.9	17.3	1.2	1.4	19.1	6.2	0.7	14.2	0.9	1.1
738	23.7	8.7	1.4	8.1	1.4	1.7	19.9	7.9	1.2	7.2	1.2	1.4
751	52.6	23.7	3.2	2.5	3.5	3.9	50.2	26.7	3.3	2.3	4.1	4.8
781	20.7	9.3	1.4	10.7	1.2	1.4	19.0	10.6	1.6	9.3	1.4	1.5
783	18.6	8.9	1.0	4.8	1.1	1.3	19.3	8.9	1.0	4.9	1.2	1.4
784	21.7	6.0	0.8	6.2	0.8	1.1	21.7	6.0	0.8	6.2	0.8	1.1
794	38.3	25.5	2.0	7.7	2.0	2.2	39.9	26.5	2.2	7.3	1.7	1.9
799	32.9	10.3	1.3	10.1	1.4	1.6	21.9	8.7	0.9	7.2	1.2	1.3
800	14.0	10.5	0.9	5.7	1.0	1.2	14.7	10.4	0.9	6.0	1.0	1.2
801	21.0	13.8	1.6	5.8	1.6	1.8	20.5	13.2	1.2	4.2	1.3	1.5
805	22.4	15.0	1.7	5.7	1.6	1.8	17.9	11.6	1.4	4.7	1.4	1.6
806	31.6	17.9	2.2	5.7	2.3	2.5	29.2	18.0	2.3	4.6	2.4	2.6
807	35.8	11.3	2.0	10.1	2.3	2.6	25.8	7.9	1.8	8.7	1.2	1.5

808	34.2	16.0	2.6	6.6	2.7	2.9	31.3	16.3	2.4	6.5	2.6	2.8
809	22.0	8.4	1.2	8.7	1.4	1.6	16.3	7.1	1.1	7.6	1.1	1.3
820	33.0	7.0	1.7	10.3	1.9	2.2	21.9	6.1	1.1	9.0	1.5	1.8
830	19.7	11.9	0.7	8.5	0.9	1.1	20.6	12.9	0.8	7.9	0.9	1.2
870	32.1	6.2	1.1	15.4	1.3	1.6	33.5	4.6	1.0	16.5	1.3	1.5
871	29.2	21.9	2.2	6.9	2.4	2.6	27.1	20.4	2.3	7.1	2.5	2.8
872	29.9	10.8	1.2	10.0	1.4	1.7	34.5	9.8	1.1	8.8	1.3	1.5
873	35.2	13.9	1.3	12.3	1.7	2.1	30.8	11.4	1.2	12.0	1.8	2.0
874	25.3	11.5	1.4	9.0	1.5	1.7	23.6	10.1	1.2	7.2	1.3	1.6

7.5 Large Sample Analysis – Sample B Valuation Error Descriptive Statistics

Table 26 - Sample B Valuation Error Descriptive Statistics

Panel A: Pooled Sample B	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	5263	-0.1096	0.4340	-0.0349	-2.6551	-0.2740	0.1628	0.6996
P/E Absolute Error (ABSERROR_PE)	5263	0.3048	0.3278	0.2123	0.0001	0.0943	0.3965	2.6551
RIM Signed Error (SE_VAL_RIVM)	5263	-0.1040	0.4169	-0.0391	-1.8930	-0.3098	0.1758	0.6806
RIM Absolute Error (AE_VAL_RIVM)	5263	0.3136	0.2936	0.2353	0.0002	0.1075	0.4254	1.8930

Panel B: Sub-Sample B_L	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	2633	-0.2312	0.4607	-0.1244	-2.6551	-0.3948	0.0478	0.6879
P/E Absolute Error (ABSERROR_PE)	2633	0.3378	0.3893	0.2074	0.0001	0.0887	0.4289	2.6551
RIM Signed Error (SE_VAL_RIVM)	2633	-0.2750	0.4306	-0.1975	-1.8930	-0.5004	0.0246	0.6704
RIM Absolute Error (AE_VAL_RIVM)	2633	0.3701	0.3522	0.2562	0.0002	0.1154	0.5064	1.8930

Panel B: Sub-Sample C_H	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	2630	0.0122	0.3673	0.0635	-2.5927	-0.1575	0.2535	0.6996
P/E Absolute Error (ABSERROR_PE)	2630	0.2717	0.2474	0.2172	0.0007	0.0988	0.3724	2.5927
RIM Signed Error (SE_VAL_RIVM)	2630	0.0670	0.3220	0.0977	-1.7494	-0.1038	0.2925	0.6806
RIM Absolute Error (AE_VAL_RIVM)	2630	0.2572	0.2050	0.2165	0.0002	0.1006	0.3654	1.7494

7.6 Large Sample Analysis – Sample C Valuation Error Descriptive Statistics

Table 27 - Sample C Descriptive Statistics

Panel A: Pooled Sample C	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	5198	-0.1084	0.4310	-0.0343	-2.6551	-0.2722	0.1627	0.6996
P/E Absolute Error (ABSERROR_PE)	5198	0.3032	0.3249	0.2117	0.0001	0.0937	0.3947	2.6551
RIM Signed Error (SE_VAL_RIVM)	5198	-0.1042	0.4172	-0.0395	-1.8930	-0.3099	0.1753	0.6806
RIM Absolute Error (AE_VAL_RIVM)	5198	0.3137	0.2941	0.2350	0.0002	0.1073	0.4254	1.8930

Panel B: Sub-Sample C_L	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	2625	-0.2503	0.4603	-0.1604	-2.6551	-0.4343	0.0376	0.6879
P/E Absolute Error (ABSERROR_PE)	2625	0.3573	0.3833	0.2328	0.0001	0.1058	0.4602	2.6551
RIM Signed Error (SE_VAL_RIVM)	2625	-0.2785	0.4267	-0.2035	-1.8930	-0.5006	0.0176	0.6432
RIM Absolute Error (AE_VAL_RIVM)	2625	0.3698	0.3505	0.2584	0.0002	0.1183	0.5043	1.8930

Panel C: Sub-Sample C_H	**N**	**Mean**	**Standard Deviation**	**Median**	**Minimum**	**Q1**	**Q3**	**Maximum**
P/E Signed Error (SERROR_PE)	2573	0.0364	0.3429	0.0713	-2.5927	-0.0986	0.2509	0.6996
P/E Absolute Error (ABSERROR_PE)	2573	0.2480	0.2395	0.1903	0.0001	0.0832	0.3411	2.5927
RIM Signed Error (SE_VAL_RIVM)	2573	0.0737	0.3213	0.1027	-1.7494	-0.0918	0.2978	0.6806
RIM Absolute Error (AE_VAL_RIVM)	2573	0.2564	0.2071	0.2131	0.0005	0.0980	0.3724	1.7494

7.7 Large Sample Analysis – Sample A Valuation Error Descriptive Statistics by SIC3

Table 28 - Sample A Descriptive Statistics by SIC3

Pooled Sample A	Mean				Median			
3-Digit SIC	P/E SE	P/E AE	RIM SE	RIM AE	P/E SE	P/E AE	RIM SE	RIM AE
104	-0.1309	0.4179	-0.1829	0.4291	0.0587	0.3787	-0.1201	0.3324
122	-0.0356	0.1811	-0.4567	0.4932	0.0298	0.1573	-0.3917	0.3917
131	-0.2448	0.4392	-0.0869	0.3706	-0.1813	0.3458	0.0177	0.2985
138	-0.1630	0.2867	-0.5403	0.5566	-0.1092	0.2184	-0.4623	0.4623
140	-0.1073	0.3338	-0.0202	0.2851	-0.1001	0.2508	-0.0338	0.1973
153	0.1156	0.2932	0.0183	0.2361	0.0987	0.2427	0.0632	0.1637
160	-0.0603	0.1823	-0.1061	0.1852	-0.0485	0.1243	-0.0280	0.1158
162	-0.0264	0.2716	-0.1713	0.3184	0.0506	0.2172	-0.2501	0.2734
170	0.1481	0.2877	-0.4405	0.4633	0.2256	0.3111	-0.4612	0.4612
202	-0.2528	0.3796	-0.1600	0.3496	-0.3324	0.3324	-0.2052	0.3949
204	-0.0058	0.2065	-0.2973	0.2973	0.0301	0.2007	-0.2414	0.2414
205	0.1047	0.1572	0.1306	0.1712	0.1674	0.1674	0.2363	0.2363
206	-0.0088	0.1368	0.2737	0.2737	0.0594	0.0938	0.2878	0.2878
207	-0.1972	0.3445	-0.5812	0.5812	-0.2301	0.2590	-0.4008	0.4008
208	0.0311	0.1917	-0.0460	0.1849	0.0106	0.1643	-0.0805	0.1649
209	0.0197	0.4455	0.0078	0.4155	0.1160	0.4293	-0.0230	0.3709
211	-0.0292	0.1397	-0.3491	0.3674	-0.0638	0.1268	-0.3183	0.3183
227	-0.0423	0.2068	-0.1075	0.2403	0.0196	0.1964	-0.0270	0.2163
230	0.0187	0.2615	-0.0600	0.2926	-0.0562	0.1960	-0.0534	0.2466
233	0.0586	0.2695	0.0467	0.2217	0.0586	0.2695	0.0467	0.2217
240	-0.3976	0.5394	0.4185	0.4185	-0.0588	0.2128	0.4003	0.4003
242	-0.1160	0.5447	0.4084	0.4084	-0.0752	0.5795	0.3438	0.3438
245	-1.0081	1.1942	-0.0728	0.4275	-1.0081	1.1942	-0.0728	0.4275
251	-0.0824	0.2241	-0.0350	0.1374	-0.0169	0.0899	0.0110	0.0934
262	-0.3281	0.5184	-0.4559	0.4692	-0.1943	0.3497	-0.3591	0.3591
263	0.0189	0.2089	-0.1357	0.3394	-0.0678	0.2017	-0.0927	0.2758
265	-0.0889	0.4950	0.2223	0.2223	-0.4364	0.4394	0.0210	0.0210
267	0.0758	0.1785	-0.2009	0.2275	0.0944	0.1828	-0.1662	0.1686
271	-0.2881	0.4472	-0.4444	0.5546	0.0241	0.2925	-0.1741	0.2140
275	-0.0256	0.2936	-0.1756	0.3525	0.0902	0.2769	-0.0135	0.1751
278	0.0778	0.1260	-0.4645	0.4711	0.1462	0.1462	-0.0597	0.0597
280	0.0134	0.1260	-0.2026	0.2712	0.0724	0.0935	-0.1445	0.1937
281	0.0023	0.2785	-0.1766	0.3665	0.0529	0.2549	-0.0546	0.3362
282	0.0455	0.1480	-0.2873	0.3368	0.0225	0.0930	-0.2590	0.2695
283	-0.5275	0.6068	-0.1606	0.3788	-0.4771	0.4983	-0.0954	0.3132
284	-0.0605	0.2597	-0.0564	0.1949	0.0201	0.1968	0.0011	0.1648
285	0.0264	0.2615	-0.2564	0.2721	0.0475	0.1259	-0.2065	0.2065
286	-0.1244	0.3016	-0.3758	0.4246	-0.0628	0.2178	-0.2473	0.3000

287	-0.0386	0.1901	-0.2502	0.2900	-0.1082	0.1434	-0.2087	0.2137
289	-0.0338	0.2099	-0.1919	0.2717	0.0255	0.1932	-0.1871	0.2401
291	-0.0188	0.1954	-0.7166	0.7396	-0.0287	0.1484	-0.6842	0.6842
301	0.3033	0.3033	0.2548	0.2548	0.3033	0.3033	0.2548	0.2548
308	0.0016	0.2240	-0.1840	0.2941	0.0124	0.2353	-0.1466	0.2244
314	0.0112	0.2498	-0.1285	0.2591	0.0934	0.1945	-0.0854	0.1809
329	-0.0658	0.3003	-0.0905	0.2322	-0.0060	0.3072	-0.0700	0.1695
331	-0.0289	0.2225	-0.4739	0.5099	0.0001	0.1773	-0.3837	0.3837
334	-0.5182	0.5993	-0.4525	0.4525	-0.0880	0.1846	-0.4392	0.4392
335	0.0747	0.2401	-0.2067	0.3007	0.1126	0.2312	-0.1259	0.2196
339	0.0063	0.1751	-0.3572	0.3572	0.0063	0.1751	-0.3572	0.3572
341	0.0199	0.1234	-0.2832	0.2832	0.0314	0.1375	-0.2847	0.2847
342	-0.0597	0.2746	-0.2825	0.3903	-0.0214	0.2132	-0.2206	0.2750
344	0.0929	0.2769	-0.0234	0.2064	0.1035	0.2441	0.0428	0.1490
348	0.0253	0.0253	0.0461	0.0461	0.0253	0.0253	0.0461	0.0461
349	0.0436	0.2104	-0.0704	0.1929	0.0274	0.2117	-0.0661	0.1197
351	0.0476	0.0594	-0.1241	0.2236	0.0778	0.0778	-0.2226	0.2226
353	-0.0020	0.1822	-0.1165	0.2411	0.0083	0.1606	-0.0774	0.1763
354	-0.0115	0.1661	-0.1954	0.2588	0.0489	0.1487	-0.2041	0.2041
355	0.0305	0.2362	-0.0684	0.2332	0.0534	0.1581	-0.0582	0.1725
356	0.0003	0.2249	-0.0923	0.2576	0.0716	0.1965	-0.0343	0.1810
357	-0.0624	0.3060	0.0108	0.3058	-0.0101	0.2366	0.0694	0.2619
358	-0.0361	0.1824	-0.1146	0.1927	0.0094	0.1667	-0.1417	0.1743
361	-0.2688	0.2688	-0.0897	0.1361	-0.2203	0.2203	-0.1138	0.1233
362	-0.0233	0.3376	-0.5612	0.5888	0.1030	0.3300	-0.4253	0.4253
364	0.0090	0.1320	-0.1304	0.2091	0.0413	0.0738	-0.0856	0.1021
366	-0.0028	0.3218	-0.0767	0.3006	0.1216	0.2388	0.0273	0.1978
367	-0.1981	0.3476	-0.1580	0.3442	-0.0931	0.2217	-0.0446	0.2509
369	-0.1002	0.3583	-0.3920	0.4717	0.0405	0.3080	-0.2265	0.2485
371	-0.1148	0.3752	-0.2426	0.3872	0.0000	0.3158	-0.1675	0.2932
372	0.0020	0.1740	-0.3055	0.3511	0.0147	0.1432	-0.2066	0.2454
373	-0.0063	0.0970	-0.0987	0.1296	0.0111	0.0505	-0.0720	0.0829
374	-0.1440	0.3137	-0.0681	0.2178	-0.0184	0.2076	-0.0402	0.1193
379	0.0450	0.2623	-0.4374	0.4376	0.0840	0.3242	-0.4101	0.4101
381	-0.0111	0.2608	-0.1343	0.3256	0.0042	0.2637	-0.0093	0.2855
382	-0.0632	0.2331	0.0773	0.2285	-0.0460	0.1755	0.1133	0.1984
384	-0.1538	0.2888	0.1080	0.2703	-0.1423	0.2352	0.1519	0.2355
386	-1.0681	1.0681	-0.5018	0.5018	-1.0681	1.0681	-0.5018	0.5018
394	-0.0353	0.2046	-0.2906	0.3211	-0.0241	0.1856	-0.2484	0.2484
399	-0.2132	0.7112	-0.0786	0.4387	-0.1664	0.6058	-0.2077	0.4118
401	-0.0289	0.1647	-0.0493	0.2280	-0.0638	0.1682	-0.0557	0.2033
421	-0.0291	0.2075	0.0485	0.1635	0.0247	0.1620	0.0778	0.1328
440	0.0149	0.3233	-0.0736	0.2536	0.0209	0.2424	-0.0635	0.2203
441	-0.2538	0.2538	-0.4881	0.4881	-0.2187	0.2187	-0.3992	0.3992
451	-0.1040	0.4428	-0.6218	0.6638	0.0661	0.3107	-0.6613	0.6613
470	-0.2372	0.3810	-0.1289	0.2689	0.0304	0.2388	-0.0279	0.2432

473	0.0193	0.3239	0.1232	0.2523	0.1177	0.2828	0.1804	0.2167
481	-0.4424	0.5442	0.0275	0.2910	-0.3428	0.4306	0.0696	0.2505
483	-0.1943	0.4560	-0.1684	0.3771	-0.1403	0.2935	-0.0716	0.3028
484	-0.6014	0.6617	-0.0952	0.2136	-0.3246	0.3246	-0.0535	0.1033
488	-0.7663	0.7663	-0.1283	0.1884	-0.8933	0.8933	-0.0665	0.1265
489	-0.4515	0.6636	0.0179	0.3712	-0.3785	0.4728	0.0286	0.2849
491	-0.0163	0.1198	-0.1053	0.2096	-0.0240	0.0849	-0.0526	0.1297
492	-0.0117	0.1558	-0.0112	0.1700	-0.0189	0.0985	0.0098	0.1180
493	-0.0029	0.0800	-0.0693	0.1581	-0.0096	0.0667	-0.0310	0.1165
494	0.0115	0.1232	0.3088	0.3088	0.0134	0.1100	0.3155	0.3155
495	-0.0029	0.2030	0.1697	0.2246	-0.0046	0.1737	0.1959	0.2012
499	-0.0753	0.5349	0.0594	0.3805	0.1644	0.4342	0.2023	0.4516
501	-0.0041	0.1020	-0.0301	0.0527	0.0554	0.0914	-0.0406	0.0605
504	-0.1018	0.3460	-0.1439	0.2818	-0.0356	0.3270	-0.1243	0.1932
505	-0.0241	0.2445	-0.4287	0.4875	-0.0781	0.1980	-0.4937	0.4937
506	0.1615	0.2941	-0.4505	0.4672	0.1991	0.2737	-0.3395	0.3395
507	-0.0105	0.4193	-0.3612	0.4746	0.1710	0.3329	-0.2262	0.2379
508	-0.0450	0.2234	-0.3587	0.3751	-0.0580	0.1523	-0.2456	0.2456
509	-0.1723	0.5900	-0.4423	0.5255	0.1504	0.4761	-0.1533	0.2396
512	0.0108	0.2333	-0.1282	0.2032	0.0596	0.2387	-0.0200	0.0596
517	0.1244	0.3293	-0.1187	0.2584	0.2386	0.3993	-0.1517	0.2351
550	-0.0442	0.2156	-0.3745	0.4257	-0.0291	0.1931	-0.2756	0.2959
581	-0.0733	0.2655	0.0887	0.2601	-0.0735	0.2333	0.1306	0.2232
591	-0.0202	0.2114	-0.1547	0.2375	-0.0096	0.2687	-0.1868	0.2367
594	-0.0902	0.4024	-0.1048	0.3866	-0.1279	0.3144	-0.1587	0.4061
596	-0.2986	0.4657	-0.1748	0.4096	-0.2239	0.3111	-0.1105	0.3411
701	-1.0099	1.0099	0.0783	0.2348	-0.7300	0.7300	0.0908	0.2768
720	-0.0690	0.3283	0.1220	0.2726	0.0627	0.1382	0.1734	0.2568
731	-0.2020	0.3861	-0.1395	0.3654	-0.1292	0.2496	-0.0791	0.2907
732	-0.1197	0.1649	-0.2382	0.2493	-0.0428	0.1134	-0.1462	0.1462
733	-0.1219	0.3668	-0.0017	0.2530	-0.2080	0.3394	0.1386	0.2260
734	0.5712	0.5712	0.2909	0.2909	0.5712	0.5712	0.2909	0.2909
735	-0.3168	0.5056	-0.3667	0.3932	-0.1390	0.2449	-0.2778	0.2778
736	-0.0427	0.2221	-0.0174	0.2398	0.0381	0.1341	0.0242	0.1826
737	-0.0595	0.3448	0.0856	0.3306	-0.0151	0.2987	0.1566	0.3041
738	-0.1454	0.2450	-0.0856	0.2431	-0.0964	0.1566	-0.0010	0.1604
751	0.0605	0.1991	-0.1045	0.2174	0.0804	0.1868	-0.0341	0.1657
781	0.0299	0.2411	0.0017	0.2080	0.0945	0.2127	0.0817	0.1863
783	-0.7760	0.7760	-0.0047	0.2183	-0.4324	0.4324	-0.0534	0.2230
784	-0.8035	0.8035	0.3229	0.3229	-0.8035	0.8035	0.3229	0.3229
794	-0.4664	0.8483	0.0557	0.3555	0.1377	0.4247	0.2061	0.3623
799	-0.5138	0.5978	0.0523	0.3026	-0.4283	0.4954	0.1511	0.2726
800	-0.9312	1.0650	-0.1123	0.2890	-0.9183	1.0520	-0.0896	0.2663
801	-0.0571	0.2715	-0.2379	0.3827	-0.0369	0.2236	-0.1377	0.2654
805	-0.1420	0.2461	-0.2650	0.3619	-0.0373	0.1539	-0.1867	0.2605
806	-0.0699	0.1848	-0.1478	0.2538	-0.0599	0.1334	-0.1046	0.1594

807	-0.1026	0.2654	-0.0282	0.2107	-0.0715	0.1885	-0.0287	0.1972
808	0.0227	0.1533	-0.2260	0.2667	0.0691	0.1421	-0.1174	0.1580
809	-0.0860	0.2157	-0.0439	0.2390	-0.0667	0.1568	0.0213	0.1402
820	-0.0891	0.3118	-0.1660	0.3668	0.0360	0.2267	-0.0786	0.3192
830	-0.9048	0.9048	0.2665	0.2665	-0.4734	0.4734	0.3087	0.3087
870	0.0256	0.2740	0.2451	0.3107	0.1096	0.2238	0.2389	0.3187
871	-0.1064	0.3468	-0.3792	0.4878	0.0679	0.2685	-0.1190	0.2639
872	-0.1546	0.5247	0.1311	0.2207	-0.1786	0.3691	0.1400	0.1895
873	-0.1575	0.2438	0.1261	0.2441	-0.0626	0.2088	0.1773	0.2072
874	-0.0910	0.2837	0.0099	0.2361	-0.0035	0.2287	0.0505	0.2035

7.8 List of Analyst Reports Used

Table 29 – Analyst Reports Accessed

ICBSUC	Firm	Broker	Pages	Last Date Accessed	Database
1757	FERREXPO PLC	Deutsche Bank	14	20/08/2014	Thomson ONE Banker
1775	BHP BILLITON PLC	Deutsche Bank	22	20/08/2014	Thomson ONE Banker
2717	BAE SYSTEMS	Deutsche Bank	11	20/08/2014	Thomson ONE Banker
2727	VESUVIUS PLC	JP Morgan	8	20/08/2014	Thomson ONE Banker
2737	DOMINO PRINTING	Jefferies	22	20/08/2014	Thomson ONE Banker
2757	MELROSE INDUSTRIES	RBC Capital Markets	12	20/08/2014	Thomson ONE Banker
2791	RENTOKIL INITIAL PLC	Credit Suisse	20	20/08/2014	Thomson ONE Banker
3577	UNILEVER PLC	Deutsche Bank	11	20/08/2014	Thomson ONE Banker
4573	BTG PLC	JP Morgan	31	20/08/2014	Thomson ONE Banker
533	TULLOW OIL PLC	JP Morgan	17	20/08/2014	Thomson ONE Banker
533	PREMIER OIL PLC	Deutsche Bank	8	20/08/2014	Thomson ONE Banker
533	ENQUEST PLC	Credit Suisse	17	20/08/2014	Thomson ONE Banker
533	AFREN PLC	Morgan Stanley	10	20/08/2014	Thomson ONE Banker
5337	TESCO PLC	HSBC	8	20/08/2014	Thomson ONE Banker
5337	J SAINSBURY PLC	JP Morgan	8	20/08/2014	Thomson ONE Banker
5337	WM. MORRISON SUPERMT	Deutsche Bank	10	20/08/2014	Thomson ONE Banker
537	ROYAL DUTCH SHELL	Societe Generale	18	20/08/2014	Thomson ONE Banker
537	BP PLC	Societe Generale	6	20/08/2014	Thomson ONE Banker
5553	PERFORM GROUP LTD	JP Morgan	8	20/08/2014	Thomson ONE Banker
5557	TALKTALK TELECOM	Credit Suisse	9	20/08/2014	Thomson ONE Banker
573	PETROFAC LIMITED	Societe Generale	17	20/08/2014	Thomson ONE Banker
5755	CARNIVAL PLC	Morgan Stanley	51	20/08/2014	Thomson ONE Banker
5759	TUI TRAVEL PLC	JP Morgan	30	20/08/2014	Thomson ONE Banker
6535	CABLE & WIRELESS	Jefferies	18	20/08/2014	Thomson ONE Banker
6575	VODAFONE GROUP PLC	HSBC	16	20/08/2014	Thomson ONE Banker
7535	DRAX GROUP PLC	Credit Suisse	12	20/08/2014	Thomson ONE Banker
7577	PENNON GROUP PLC	RBC Capital Markets	23	20/08/2014	Thomson ONE Banker
9537	SAGE GROUP PLC	Investec	6	20/08/2014	Thomson ONE Banker
9576	ARM HOLDINGS PLC	Deutsche Bank	15	20/08/2014	Thomson ONE Banker
9576	IMAGINATION TECH GRP	JP Morgan	8	20/08/2014	Thomson ONE Banker

7.9 Small Sample Analysis - The Net Asset Value Model (NAV) and the Embedded Value Model (EmV)

The net asset value model (NAV) is essentially characterised by the fact that it simply adjusts all assets to a market value and deducts liabilities (Carmichael *et al.*, 2007). In the case of oil and gas firms it is particularly useful by calculating the reserves of such resources and assuming the firm will produce all of its reserves, until they are exhausted.

The embedded value model (EmV) is used by JP Morgan in valuing a biotechnology firm (4573). It simply computes a firm's value by working on a product by product basis and forecasting until a limited forecast horizon with the possibility of applying terminal values for products with such expected longevity (JP Morgan).

7.10 List of Annual Reports Used

Table 30 – Annual Reports Accessed

ICBSUC	Firm	Type of Report	Last Date Accessed	Database
1757	FERREXPO PLC	2013 Annual Report	23/08/2014	Perfect Information
1775	BHP BILLITON PLC	2013 Annual Report	23/08/2014	Perfect Information
2717	BAE SYSTEMS	2013 Annual Report	23/08/2014	Perfect Information
2727	VESUVIUS PLC	2013 Annual Report	23/08/2014	Perfect Information
2737	DOMINO PRINTING	2013 Annual Report	23/08/2014	Perfect Information
2757	MELROSE INDUSTRIES	2013 Annual Report	23/08/2014	Perfect Information
2791	RENTOKIL INITIAL PLC	2013 Annual Report	23/08/2014	Perfect Information
3577	UNILEVER PLC	2013 Annual Report	23/08/2014	Perfect Information
4573	BTG PLC	2014 Annual Report	23/08/2014	Perfect Information
533	TULLOW OIL PLC	2013 Annual Report	23/08/2014	Perfect Information
533	PREMIER OIL PLC	2013 Annual Report	23/08/2014	Perfect Information
533	ENQUEST PLC	2013 Annual Report	23/08/2014	Perfect Information
533	AFREN PLC	2012 Annual Report	23/08/2014	Perfect Information
5337	TESCO PLC	2014 Annual Report	23/08/2014	Perfect Information
5337	J SAINSBURY PLC	2014 Annual Report	23/08/2014	Perfect Information
5337	WM. MORRISON SUPERMT	2014 Annual Report	23/08/2014	Perfect Information
537	ROYAL DUTCH SHELL	2013 Annual Report	23/08/2014	Perfect Information
537	BP PLC	2013 Annual Report	23/08/2014	Perfect Information
5553	PERFORM GROUP LTD	2013 Annual Report	23/08/2014	Perfect Information
5557	TALKTALK TELECOM	2014 Annual Report	23/08/2014	Perfect Information
573	PETROFAC LIMITED	2013 Annual Report	23/08/2014	Perfect Information
5755	CARNIVAL PLC	2013 Form 10-K	23/08/2014	Perfect Information
5759	TUI TRAVEL PLC	2013 Annual Report	23/08/2014	Perfect Information
6535	CABLE & WIRELESS	2014 Annual Report	23/08/2014	Perfect Information
6575	VODAFONE GROUP PLC	2014 Annual Report	23/08/2014	Perfect Information
7535	DRAX GROUP PLC	2013 Annual Report	23/08/2014	Perfect Information
7577	PENNON GROUP PLC	2014 Annual Report	23/08/2014	Perfect Information
9537	SAGE GROUP PLC	2013 Annual Report	23/08/2014	Perfect Information
9576	ARM HOLDINGS PLC	2013 Annual Report	23/08/2014	Perfect Information
9576	IMAGINATION TECH GRP	2013 Annual Report	23/08/2014	Perfect Information

7.11 Small Sample Analysis - Description of Dominant Nonfinancial and Financial Justifications in Analysts' Reports

Table 31 – Dominant Valuation Justifications in Analysts' Reports

Panel A: Dominant Nonfinancial Justifications
External market analysis
Discussion of new CEO and future turnaround analysis
Broad outlook
Analysis of new strategy and its implementation
Analysis of uncertainty surrounding the industry
Nonfinancial Analysis of commercial synergies
Analysis of bookings and demand for beds
Analysis of strategy
Analysis of production
Analysis of court decision
Analysis of Joint Venture
Analysis of competitors acquisitions
Analysis of ARPU and customer base

Panel B: Dominant Financial Justifications
EBITDA analysis
Profit analysis
Analysis of interim results and forecasts
Revenue Analysis
Forecasted earnings analysis
Analysis of future revenue and investment
Free Cash Flow analysis
Cash generation analysis
Working capital analysis
Financial synergies analysis