2 Literature Review

In this section, the link between accounting numbers and equity value is evaluated as well as different valuation approaches are introduced. Furthermore, prior research about the performance of the different valuation methods is discussed.

2.1 Relation between Accounting Numbers and Stock Prices

The accounting net income (NI) of a firm, often referred to as earnings, is the "bottom line" in financial statements and a measure of firm performance. Earnings numbers measure the financial performance of a firm over a specified period and are, unlike cash flows, accrual based. In theory, NI symbolizes a change in value to common equity holders (Nichols and Wahlen 2004). Beaver (1998) developed three links through which earnings are directly related to intrinsic equity value in theory. First, reported earnings provide information about current as well as expected future profitability. Second, expected future profitability provides useful information to forecast expected future dividends. Finally, expected future dividends can be discounted to determine an intrinsic equity value.

Earnings are usually considered as the most relevant information of financial statements and hence, many equity valuation models use expected earnings as the explanatory variable (Lev 1989). Already Miller and Modigliani (1966) used expected earnings to estimate the cost of capital for the electric utility industry. However, Lev (1989) raised the question if earnings are useful to investors and contain relevant information.

Ball and Brown (1968) provided the first empirical research about the relative importance of NI. They found that stock prices react to differences between actual income numbers and expected income in the same direction. However, most of the information contained in the reported income is already incorporated in the stock price during the period prior to the announcement. Beaver (1968) observed stock prices and trading volumes around the earnings announcement periods. He discovered above normal price reactions and trading volumes around the announcement date, which is consistent with the contention that earnings include relevant information. Moreover, he provided evidence that earnings announcements let not only individual investors alter investment decisions but also change the entire market expectation. In addition, he observed lower trading volume prior to the announcement indicating that investors postpone trading decisions until the information release.

While those two papers represent the first empirical research attempts in this topic, Nichols and Wahlen (2004) provided more recent evidence on the connection between earnings and share price. They found that firms with increasing earnings experience higher abnormal stock returns than firms with decreasing earnings. More importantly, they discovered that earnings provide more value-relevant information than operational cash flows indicating that accrual accounting contains value relevant information.

However, there is criticism regarding the use of earnings in valuation. Lev (1989) argued that earnings have relatively low explanatory power for stock returns given several reasons including investor irrationality but also low information content of earnings. The low quality of earnings may be a result of data manipulation by managers as well as biases induced by valuation principles and accounting measurement.

2.2 Equity valuation principles

Since maximizing firm value is still considered as a main goal of managers, valuing a firm and correspondingly its equity is of interest for nearly every business decision inside a company. In addition, outside of a company, investors and their security analysts or credit analysts as well as potential acquirers are particularly interested in a firm´s valuation in order to support investment or acquisition decisions (Palepu, Healy et al. 2013).

According to Palepu, Healy et al. (2013) "Valuation is the process of converting a forecast into an estimate of the value of the firm´s assets or equity." However, many different valuation methods exist, and the question arises, which of the methods are the most appropriate to use. The different methods can mainly be separated into two approaches: FBVMs and MBVMs. FBVMs discount forecasted future accounting flows to estimate the intrinsic value of equity. On the contrary, MBVMs use a performance measure as a value driver of the firm and multiply it with a price multiple derived from comparable firms (Palepu, Healy et al. 2013). Theoretically, the accounting flows must be forecasted to infinity to come to the same valuation for the FBVMs (Penman and Sougiannis 1998). However, only an analysis over a finite horizon is practical which causes differences in the valuation.

2.2.1 Equity and entity perspective

For all valuation approaches two different perspectives of valuation exist: equity and entity perspective. The equity perspective directly evaluates shareholder´s value of equity claims (Palepu, Healy et al. 2013). However, in a world with taxes, cost of financial distress and other agency costs different capital structures affect the value of a firm and hence also equity value. Valuing all operating and investment assets of the firm (entity perspective) meaning the claims of equity holders as well as debt holders is therefore less affected by decisions regarding the capital structure. Generally, the relation between equity- and entity value can be described as followed (Schreiner and Spremann 2007):

$$V_{entity} = V_{equity} + V_{net\ debt} \tag{1}$$

$$V_{net\ debt} = V_{total\ debt} - V_{cash\ \&\ cash\ equivalents} + V_{preferred\ stock} \tag{2}$$

where

V_{entity}	Enterprise value
V_{equity}	Market value of common equity
$V_{net\ debt}$	Market value of net debt
$V_{total\ debt}$	Market value of total debt
$V_{cash\ \&\ cash\ equivalents}$	Market value of cash and cash equivalents
$V_{preferred\ stock}$	Market value of preferred stock

In theory, both perspectives lead to the same result, but there are implementation issues which affect practical performances (Palepu, Healy et al. 2013). The entity value cannot be observed since debt is usually not stated as market value and is approximated by book values. Especially interest rate changes and default risk developments but also differences in accounting practices can create large variations in such approximation (Schreiner and Spremann 2007).

Given those implementation issues, this dissertation only considers the equity perspective for simplification reasons. In a next step, three different FBVMs and one MBVM are introduced and their advantages as well as disadvantages are discussed.

2.3 Flows-based Model

2.3.1 Dividend Discount Model

In theory, the value of a financial asset is the present value of the net cash flows generated by the asset. The dividend discount model (DDM) follows the assumption that the cash payoffs ultimately received by shareholders for their equity claims are the dividends paid by the firm. Therefore, the present value of all expected future dividends represents the value of equity (Palepu, Healy et al. 2013):

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

where

V_t^e	Present value of all future dividends
$E_t[DIV_{t+1}]$	Expected dividend paid in one year from now
r_e	Cost of equity which is the relevant discount rate that represents the riskiness of expected dividends

Equation (3) assumes an infinite lifetime of the firm, but this might not be true e.g. if the firm goes bankrupt. In addition, this assumption is impractical as it is more difficult to forecast longer horizons. Assuming a constant growth rate g of future dividends in perpetuity simplifies the equation (Palepu, Healy et al. 2013):

$$V_t^e = \frac{E_t[DIV_{t+1}]}{r_e - g} \tag{4}$$

Combining equation (3) and (4) and assuming dividends will grow at a constant rate after two years from now allows to shorten the forecasting period (Palepu, Healy et al. 2013):

$$V_t^e = \frac{E_t[DIV_{t+1}]}{1+r_e} + \frac{E_t[DIV_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[DIV_{t+2}]\times(1+g)}{r_e-g}}{(1+r_e)^2} \tag{5}$$

Now, the constant growth model represents a terminal value (TV), which simplifies the model and allows analysts to forecast short-term or medium-term dividends.

The implementation of a DDM is rather simple given its basis that dividends are the ultimate cash flows to shareholders. In addition, it is practical to apply for mature firms, which pay stable dividends as those are easier to forecast. However, the model is limited to dividend paying firms but the amount of dividends paid highly depends on a firm´s investment opportunities (Palepu, Healy et al. 2013). Thus, start-ups or quickly developing firms, which require capital and do not pay dividends, cannot be valued with a DDM. In addition, Ball and Brown (1968) provided evidence for a connection between NI and stock price returns. Nevertheless, dividends may not be perfectly linked to earnings since also firms with negative earnings pay dividends, which may decrease the accuracy of the DDM. Moreover, Francis, Olsson et al. (2000) discovered a high dependence on the TV in this model. Hence, changes in the estimates of the constant growth rate g and/or the cost of equity r_e result in large changes in the TV and correspondingly in the equity value estimate. Given this sensitivity, difficulties in estimating g and r_e accurately have a large impact on the accuracy of the value estimate. Furthermore, the assumption of a constant perpetual growth rate of the dividends is often unrealistic.

2.3.2 Discounted Free Cash Flow Model

The discounted free cash flow model (DFCFM) follows the same basic theory for the value of financial claims – present value of future net cash flows – as the DDM. However, the corresponding accounting flow differs. Instead of discounting dividends, free cash flows either to equity (FCFE) or to entity/firm (FCFF) are considered. As mentioned earlier, this dissertation focuses only on the equity perspective and thus only FCFE is considered, which is also important for choosing the correct discount rate. FCFE is the cash flow remaining after meeting all debt payments and investment needs and thus is the amount available to be distributed to shareholders (Damodaran 2010). Thus, this approach tries to account for the fact that many firms do not pay any dividends although they create sufficient FCFE. Over the entire lifetime of a firm, total FCFE and dividends should be the same under the assumption, that all FCFE are ultimately distributed to shareholders.

The FCFE for a period *t* can be calculated by adjusting NI for all non-expense cash outflows and all non-cash earnings (Palepu, Healy et al. 2013):

$$FCFE_t = NI_t + D\&A_t - CAPEX_t - \Delta WC_t + \Delta BVD_t \quad (6)$$

where

NI_t	Net income during period *t*
$D\&A_t$	Depreciation and amortization expense (D&A) during period *t*
$CAPEX_t$	Capital expenditure during period *t*
ΔWC_t	Change in working capital (WC) during period *t*
ΔBVD_t	Change in book value of debt (BVD) during period *t*

Using again the assumption of a constant growth rate after two years, results in following calculation of the intrinsic value of equity (Palepu, Healy et al. 2013):

$$V_t^e = \frac{E_t[FCFE_{t+1}]}{1+r_e} + \frac{E_t[FCFE_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[FCFE_{t+2}]\times(1+g)}{r_e-g}}{(1+r_e)^2} \quad (7)$$

The DFCFM overcomes the implementation issue of the DDM that it is also applicable for non-dividend paying firms. Additionally, as it focuses on cash flows, that are available for distribution to shareholders and not only on dividends, it is a less conservative approach and is expected to generate a more accurate estimate (Damodaran 2010). Moreover, FCFE are less discretionary than earnings and thus overcome the issue of possible earnings manipulation mentioned by Lev (1989). Analysts seem to recognize those advantages as the DFCFM is widely used in the financial industry (Hand, Coyne et al. 2017).

However, like the DDM, DFCFM is very sensitive to assumptions about the input factors given the high dependence on TV (Francis, Olsson et al. 2000). Moreover, forecasting FCFE can cause difficulties whenever items such as working capital are difficult to identify or financial leverage is likely to change over time (Damodaran 2010).

2.3.3 Residual Income Valuation Model

Although the residual income valuation model (RIVM) has not recently been developed (Preinreich 1938), it is often attributed to the rediscovery by Ohlson (1995). The model assumes that earnings, dividends, and book value of equity (BVE) are connected through the clean surplus relation (CSR):

$$\Delta BVE_t = NI_t - DIV_t \tag{8}$$

$$DIV_t = NI_t + BVE_{t-1} - BVE_t \tag{9}$$

where

DIV_t	Dividend paid (net of capital distributions) during period *t*
NI_t	Net income during period *t*
ΔBVE_t	Change in BVE over the period *t*

The CSR holds, if all changes in assets and liabilities unrelated to dividends go through the income statement. Replacing dividends in (3) of the DDM results in:

$$V_t^e = \frac{E_t[NI_{t+1}]+BVE_t-BVE_{t+1}}{1+r_e} + \frac{E_t[NI_{t+2}]+BVE_{t+1}-BVE_{t+2}}{(1+r_e)^2} + \frac{E_t[NI_{t+3}]+BVE_{t+2}-BVE_{t+3}}{(1+r_e)^3} + \cdots \tag{10}$$

Which can be reformulated as:

$$V_t^e = BVE_t + \frac{E_t[NI_{t+1}]-r_e \times BVE_t}{1+r_e} + \frac{E_t[NI_{t+2}]-r_e \times BVE_{t+1}}{(1+r_e)^2} + \frac{E_t[NI_{t+3}]-r_e \times BVE_{t+2}}{(1+r_e)^3} + \cdots \tag{11}$$

The numerator in each fraction represents the expected residual income (RI) for each period. It is the difference of expected earnings and required earnings calculated as the product of a required return and the BVE at the beginning of the period (Ohlson 1995). Assuming RI will grow at a constant rate *g* after two years results in following equation including a TV:

$$V_t^e = \mathrm{BVE}_t + \frac{E_t[RI_{t+1}]}{1+r_e} + \frac{E_t[RI_{t+2}]}{(1+r_e)^2} + \frac{\frac{E_t[RI_{t+2}]\times(1+g)}{r_e-g}}{(1+r_e)^2} \tag{12}$$

The value created by RI represents the difference between BVE and market value of equity known as goodwill (Ohlson 1995). The rationale behind the RIVM is to focus on earnings rather than cash flows because they are the “bottom-line” in financial statements and the primary performance measure of a firm. Additionally, earnings include accruals and hence, take into account additional performance information, that cash flows cannot capture (Nichols and Wahlen 2004). This advantage can be misused and potential managerial discretionary or manipulation can lead to a less reliable value estimate. However, Francis, Olsson et al. (2000) argued that empirically the RIVM is resistant to variations in companies´ accounting policies and practices. Courteau, Kao et al. (2015) analyzed the impact of a new U.S. accounting regulation in 2002 on the performance of RIVM and DFCFM. They found that earnings management indeed affected the performance of RIVM prior to that regulation. However, post the regulation RIVM outperforms DFCFM also for firms with potential earnings management. Francis, Olsson et al. (2000) as well as Penman and Sougiannis (1998) found a main advantage of RIVM that the TV represents only a small portion of the value estimate. A large portion is captured by BVE making the estimate less sensitive to assumptions regarding the cost of equity and the long-term growth rate. Thus, they argued that the RIVM generates a more reliable estimate.

Nevertheless, in practice CSR might not hold. Lo and Lys (2000) discovered that a significant number of companies which use US GAAP as accounting standard violate CSR historically. Main reason for this is that besides NI other comprehensive income affects the change in BVE (Spiceland, Sepe et al. 2013). However, Lo and Lys (2000) also stated that CSR must only hold for expected future values.

2.4 Multiples-based Model

MBVMs are widely used among practitioners. 99.1% of analysts use some kind of earnings multiple in their valuation process (Asquith, Mikhail et al. 2005). This popularity is among other reasons given by the simplicity of the concept of MBVMs. It is very easy to understand and to calculate (Fernandez 2001). Unlike FBVMs, this approach does not require to forecast accounting flows and to calculate the present value using an estimated required return. MBVMs follow the assumption that the ratio of the price and a performance measure of the firm being valued will revert to a benchmark ratio (Courteau, Kao et al. 2006). Thus, in

MBVMs a performance measure is chosen as a value driver and multiplied by a corresponding multiple of comparable firms (Liu, Nissim et al. 2007):

$$V_i^e = VD_i \times BenchmarkMultiple_i(\Phi_i) \tag{13}$$

where

V_i^e	Estimated intrinsic value of equity of firm *i*
VD_i	Value driver of firm *i*
Φ_i	Set of *n* comparable firms for firm *i*

To calculate the benchmark multiple, a multiple for each comparable firm is calculated as followed:

$$Multiple = \frac{P_j}{VD_j} \tag{14}$$

Where

P_j	Observed share price
VD_i	Value driver of the j^{th} comparable firm with $j=1,2,\ldots,n$

Using the multiples calculated for comparable firms, a benchmark multiple can be determined. For this, analysts often use the mean or median but there are also other methods which can affect the accuracy of valuation (Liu, Nissim et al. 2007).

Therefore, this valuation method requires three main decisions (Baker and Ruback 1999):

1. Choice of the value driver
2. Choice of the comparable firms
3. Choice of the calculation method of the benchmark multiple

Since MBVMs rely on the current valuation of comparable firms, they have the ability to capture the current mood of stock markets better than FBVMs (Baker and Ruback 1999). However, this advantage can cause issues at the same time. If the chosen comparable firms – e.g. industry – are over- or undervalued, the value estimates are distorted in the same direction.

2.4.1 Choice of the value driver

Many different multiples using a wide range of value drivers exist. According to Fernandez (2001) the most commonly used ones are the price earnings ratio (PER) and enterprise value to EBITDA (EV/EBITDA) multiple. The choice of the value driver directly affects the value estimate and thus should be done carefully. No basic rules apply, which determine the correct value driver and they may perform best for different firms and industries (Kim and Ritter 1999). The value driver only needs to satisfy two conditions:

Since negative equity values do not exist, the value driver must take a positive value (Liu, Nissim et al. 2007). Moreover, the value driver should be proportional to the stock price.

According to Nichols and Wahlen (2004) earnings contain more value relevant information than cash flows because accruals contain additional information about profitability and wealth creation. Hence, multiples including earnings rather than cash flows should result in a more accurate value estimate. Nevertheless, Beaver and Morse (1978) argued that accounting methods regarding accruals or transitory items cause differences in PER. To circumvent such issues, rather forecasted instead of realized earnings should be used. Several studies found that forecasted earnings improve the accuracy of MBVMs (Kim and Ritter 1999, Lie and Lie 2002, Liu, Nissim et al. 2002).

Liu, Nissim et al. (2002) compared the valuation performance of a wide range of multiples using different value drivers. They found that using a multiple horizon forecast can even improve the accuracy of the value estimate. Furthermore, they showed that realized earnings multiples perform better than realized cash flow multiples illustrating the value relevant information contained in accruals. In a more specific analysis a few years later, they showed that this is also the case for forecasted value drivers and argue that earnings indicate changes in value independent from incoming cash flows (Liu, Nissim et al. 2007). Finally, they argued that forecasted earnings multiples perform best among all analyzed industries rejecting the hypothesis that in different industries different multiples perform best.

To conclude, although it is argued that accruals can be used for earnings manipulation and require managerial discretion, empirical evidence suggest that a forecasted earnings multiple performs best among MBVMs (Liu, Nissim et al. 2007).

2.4.2 Choice of the comparable firms

Different studies have shown that the level of comparability of the firm being valued and the comparable firms affect the accuracy of the value estimate using a MBVM (Boatsman and Baskin 1981, Alford 1992, Bhojraj and Lee 2002). The benchmark multiple calculated from comparable firms should be similar to the unknown multiple of the firm being valued (Alford 1992). First it is questioned if only one comparable firm or a group of comparable firms should be used. Since multiples can vary a lot among different companies, using a group as peer can reduce the effect of outliers and hence lead on average to a more accurate value estimate. However, if only one comparable firm is chosen which is the most similar to the firm being valued, the value estimate in that specific case can be the most accurate.

Choosing the industry as peer group seems reasonable and is found to be an effective approach. Alford (1992) discovered that choosing the peer group by industry results in similar accuracy as selecting the comparable firms based on risk and earnings growth, suggesting that the industry can capture those two properties. However, adjusting for leverage decreases accuracy. Boatsman and Baskin (1981) compared the value estimate using a PER but two different comparable firms. They found that the value estimate was more accurate when the comparable firm was specifically chosen from the industry based on the most similar ten-year earnings growth rate instead of randomly choosing an industry member. On the contrary, Alford (1992) could not find improvements of dividing the industry by earnings growth which supports the idea of using a group of firms can reduce the effect of outliers. Besides similar economic characteristics, Young and Zeng (2015) argued that the comparability of accounting increases the accuracy of MBVMs and thus needs to be considered in peer selection.

Bhojraj and Lee (2002) developed a different approach for selecting a peer group. They argued that selecting comparable firms based on a “warranted multiple” which is estimated by using variables that affect the value driver – e.g. expected profitability or growth – results in a more accurate value estimate than the selection simply based on the industry. Hence, they focused on choosing firms that are similar regarding profitability, risk characteristics and growth. This should circumvent the issue that the industry may not always be concretely defined.

The correct choice of comparable firms is a crucial factor in MBVMs since it significantly affects the accuracy of the value estimate. Difficulties in the selection process can cause the value estimate to be imprecise.

2.4.3 Choice of the calculation method of the benchmark multiple

After calculating the chosen multiple for each of the chosen comparable firms, the benchmark multiple can be calculated. Hereby, the choice of the averaging technique matters as it has a large impact on the results (Agrrawal, Borgman et al. 2010). Besides using the arithmetic mean, value-weighted mean, median, and the harmonic mean can be used (Baker and Ruback 1999):

$$arithmetic\ mean = \frac{1}{n}\sum_{j=1}^{n}\frac{P_j}{VD_j} \tag{15}$$

$$value - weigthed\ mean = \frac{\sum_{j=1}^{n}P_j}{\sum_{j=1}^{n}VD_j} \tag{16}$$

$$median = median(\frac{P_j}{VD_j}) \tag{17}$$

$$harmonic\ mean = \frac{n}{\sum_{j=1}^{n}\frac{VD_j}{P_j}} \tag{18}$$

where

n	Number of comparable firms
VDj	Value driver of the j^{th} comparable firm
P_j	Observed share price

Although averaging is often considered as using the arithmetic mean, this method does not adjust for outliers leading to an upwards biased valuation (Agrrawal, Borgman et al. 2010). To overcome such upwards bias, Damodaran (2016) proposed to use either the median, an aggregate multiple, or the inverse of a multiple, which is the harmonic mean. Baker and Ruback (1999) suggested that the harmonic mean is the best estimator because increasing prices tend to increase pricing errors. They argued that the harmonic mean is mathematically always smaller than the arithmetic mean and thus is less upwards-biased. In addition, a small value driver yields a large multiple, which the harmonic mean circumvents. Liu, Nissim et al. (2002) found similar results indicating that the harmonic mean results in more accurate value estimates than the arithmetic mean or median. Schreiner´s and Spremann´s (2007) superior results of using the median indicate that besides the harmonic mean, the median is an appropriate method, as well.

2.5 Empirical evaluation of different valuation methods

Equity valuation based on accounting numbers has been discussed by accounting researches as well as practitioners intensely. The discussion about FBVMs has intensified especially after the rediscovery of the RIVM by Ohlson (1995). Frankel and Lee (1998) observed a high correlation of a value estimate using the RIVM and stock prices. They found that a ratio of this estimate to price has the ability to predict long-term cross-sectional returns and captures effects, which cannot be explained by other common information such as a book-to-market ratio or beta. Penman and Sougiannis (1998) as well as Francis, Olsson et al. (2000) compared the performance in value estimation of DDM, DFCFM, and RIVM in a LSA. Despite the theoretical equivalence of the three models, they found a superiority in accuracy of RIVM. They named the lower portion of TV in the RIVM (Francis, Olsson et al. 2000) and the additional information of earnings using accruals (Penman and Sougiannis 1998) as major reasons for this superiority. However, as a response to those findings Lundholm and O'keefe (2001) argued, that three implementation errors were made causing such inequivalences of RIVM and DFCFM. Empirical evidence on the equivalence of RIVM and DFCFM was provided by Courteau, Kao et al. (2001), which analyzed the differences in DFCFM and RIVM including theoretical “ideal” TVs. However, they state, that if those “ideal” values are not available RIVM is superior to DFCFM supporting the findings of Penman and Sougiannis (1998) and Francis, Olsson et al. (2000).

Besides, MBVMs have been analyzed by researches, as well. Schreiner and Spremann (2007) analyzed European equity markets and found that multiples using the equity perspective outperform multiples using the entity perspective. Liu, Nissim et al. (2002) compared the performance of different multiples and discovered that price to forward earnings ratios outperform all other common multiples in equity valuation. They supported this finding themselves with a second study only comparing forward earnings with forward cash flows as value drivers (Liu, Nissim et al. 2007). They conclude that earnings outperform other value drivers since they include more value-relevant information through accruals. The discovery that forecasted value drivers outperform historical ones was also found by several other studies (Kim and Ritter 1999, Lie and Lie 2002, Schreiner and Spremann 2007).

The research on the direct comparison of the performance of MBVMs and FBVMs is rather limited. Lee and Swaminathan (1999) created a RIVM estimate to price multiple and found a superiority compared to the inverses of common multiples such as PER or market-to-book in predicting overall returns of the Dow Jones index. Kaplan and Ruback (1995) found that

DFCFMs lead to reliable estimates in valuing firms as part of highly levered transactions. They argued that a DFCFM performs at least as well as MBVMs. Courteau, Kao et al. (2006) compared value estimates of RIVM to a MBVM using a forward PER as value driver. They found an outperformance of the RIVM, meaning lower pricing errors and a higher ability to predict returns. Furthermore, they suggested that a combination of both value estimates using equal weights results in the most accurate valuation.

2.6 Hypothesis development

Although in theory different valuation approaches should lead to the same value estimate (Demirakos, Strong et al. 2010, Palepu, Healy et al. 2013) in practice this highly depends on the consistency of implementation and is therefore highly discussed among researchers (Penman and Sougiannis 1998, Francis, Olsson et al. 2000, Lundholm and O'keefe 2001). This dissertation aims to provide evidence on whether the reliability of the intrinsic value estimates derived from a MBVM and three FBVMs differ. Additionally, if a difference is found, the dissertation intends to suggest which of the analyzed models performs best.

Based on prior empirical research results, two hypotheses are developed. The first one distinguishes whether MBVMs or FBVMs are more reliable. The second one, then focuses on which specific approach performs the best. Those hypotheses will then be examined in a LSA.

Courteau, Kao et al. (2006) found that a direct valuation based on a version of the RIVM leads to lower prediction errors compared to value estimates based on a price to aggregated forecasted earnings multiple. Hence, it is suggested, that even when a multiple horizon forecast for earnings is used for the MBVM as suggested by Liu, Nissim et al. (2002), the flows-based approach leads to a more accurate value estimate. Since MBVMs are based on the idea that the target firm´s multiple will revert to the average of comparable firms (Courteau, Kao et al. 2006), the accuracy of the value estimates highly depends on the choice of comparable firms (Alford 1992). Therefore, if an appropriate peer group cannot be identified or stock prices of the peer group are highly over- or undervalued, value estimates generated by MBVMs are less reliable. Furthermore, firm specific factors such as risk and long term growth are more likely to be captured using a FBVM (Demirakos, Strong et al. 2010). This is supported by the findings of Frankel and Lee (1998) as well as Lee and Swaminathan (1999), that a more complete valuation approach based on the RIVM is a superior stock return predictor than common multiples such as book-to-market or earnings-to-price ratios. Given the dependence of MBVM on the valuation of comparable firms and the ability of FBVMs to capture more firm specific information leads to following hypothesis:

H1: Flows-based models perform better in equity valuation than multiple-based models

Moreover, it is questioned which of the FBVMs performs best. Although the DDM is very practical as it values the expected cash flows received by shareholders, the model is very limited to only dividend paying firms. In addition, Francis, Olsson et al. (2000) discovered, that TV represents a high portion of value estimate in that model, which makes it more sensitive to assumptions regarding the long term growth and the discount rate. Compared to the DDM, the DFCFM is applicable for non-dividend paying firms and is less conservative as all cash flows available for distribution to shareholders are considered (Damodaran 2010). However, its main advantage is the focus on cash flows, which overcomes the issue of potential earnings management. Nevertheless, the DFCFM also faces issues regarding a high portion of TV (Francis, Olsson et al. 2000) and in addition, forecasting FCFE may causes difficulties given possible changes in financial leverage or challenges in the identification of items such as working capital (Damodaran 2010). The RIVM can overcome those issues as BVE, which is more reliable than forecasted values, represents a high portion of value estimates and reduces the impact of TV (Francis, Olsson et al. 2000). Furthermore, earnings forecasts are expected to be more precise and predictable than forecasts of FCFE. Moreover, Penman and Sougiannis (1998) see accrual based accounting measures as a reason for the superiority of RIVM. RI includes accrual information and thus contains information about future developments. Although it may be argued that accrual information allow potential earnings management and hence, less reliable estimates, Francis, Olsson et al. (2000) indicated a resistance of the RIVM to variations in companies´ accounting policies and practices. Therefore, given the low portion of RIVM compared to DDM and DFCFM, the additional information contained in accrual accounting considered in RIVM, as well as the implementation issues faced by DDM and DFCFM leads to the second hypothesis:

H2: Among flows-based models, the residual income valuation method performs best

2.7 Conclusion of the literature review

Summarizing the previous section, accounting information takes an important role in part of equity valuation. As discussed, the performance of different valuation models has been discussed intensely among researchers, although in theory such models lead to the same estimate. As a next step, those performances will be analyzed in a LSA.

3 Large Sample Analysis

3.1 Methodology

In order to evaluate the performance of the three presented FBVMs and the chosen MBVM – price to one year ahead earnings forecast (PE1) – the different models are applied to a large sample of U.S. public firm data and stock values are estimated over the observation period from 2005 to 2015. All estimations take place at the end of four month after fiscal year ends, which is when I/E/B/S consensus forecast numbers and other relevant data are available. Then, those value estimates are compared to market prices and evaluated on the three levels - bias, accuracy and explainability - as introduced by Francis, Olsson et al. (2000). The comparison to market prices assumes efficient markets (Courteau, Kao et al. 2006)[1].

3.1.1 Sample and Data

The required data can be collected from different data platforms: consensus earnings and dividend forecasts from *I/E/B/S*, BVE, NI, D&A, Capex, current assets (CA), current liabilities (CL), debt in CL, total assets (TA), total ordinary equity (BVE), common shares outstanding, split adjustment factors, as well as research and development expense (R&D) from *Compustat*, market prices four month after fiscal year ends, beta, as well as annual US inflation rates from *CRSP*, and risk-free rates from the *U.S. Federal Reserve Bank*. An overview of the different variables can be found in Appendix A.

The observation period starts in 2005 and ends in 2015. The dataset includes all observations of U.S. public firms over this period from those data platforms. On average there are 3,360 firm observations per year resulting in a total of 36,961 initial firm observations.

The initial sample is adjusted as shown in table 1 leaving a final sample of 11,572 observations. Finally, the observations of the accounting flows[2], BVEPS, and Prc4 are winsorized meaning extreme values are limited to either the first or 99th percentile to reduce the possible effects of extreme values.

[1] The efficient market hypothesis assumes that all relevant information is fully and correctly reflected in security prices (Timmermann and Granger 2004).

[2] EPS1, EPS2, EPS3, DPS1, DPS2, DPS3, FCFEPS1, FCFEPS2, and FCFEPS3.

Table 1

Sample selection process

Criterion	Number of observations n
Initial sample (excluding duplicates) - regulated industries (financial and utility)	**36,961** (9,256)
- missing or negative sales	**27,705** (6)
- firms with an incomplete dataset[1]	**27,699** (12,771)
- negative BVEPS	**14,928** (504)
- negative EPS1[2]	**14,424** (1,373)
- less than ten industry group observations[3]	**13,051** (1,479)
Final sample	**11,572**

[1] A complete dataset for a firm observation consists of one and two year ahead consensus forecasts of earnings per share (EPS1, EPS2) and dividends per share (DPS1, DPS2), stock price four month after fiscal year ends (Prc4), beta, BVE per share (BVEPS), and one as well as two year ahead calculated FCFE per share[3] (FCFEPS1, FCFEPS2).

[2] In order to ensure positive value estimates for the PE1 model.

[3] In order to ensure enough comparable firms for the PE1 model.

3.1.2 Model Specification

The three FBVMs, introduced in part 2.3, are performed using a two-year forecast horizon after which it is assumed that the accounting flow will grow in perpetuity resulting in a TV. Choosing the appropriate perpetuity growth rate is a key implementation issue. Many researchers use a growth rate of 4% although it is often argued that the perpetuity growth rate should be equal to the inflation rate (Penman and Sougiannis 1998, Francis, Olsson et al. 2000). Hence, in this dissertation a perpetuity growth rate equal to the median U.S. annual inflation rate between 2005 and 2015 of 1.74% is used. However, the findings are robust to changes in the growth rate to 4% and 0% as well as to expanding the forecast horizon to three years. Following the assumption of Francis, Olsson et al. (2000) that a firm cannot survive creating negative RI or FCFE over a long term horizon, negative TV estimates are set equal to zero. Furthermore, since a firm cannot contain a negative value, negative value estimates are set equal to zero, which effects 2,343 DFCFM estimates revealing an implementation issue.

[3] Description of the calculation follows in the next part.

Additionally, 4,503 firms are not expected to pay dividends over the two-year forecast horizon resulting in value estimates of zero, which demonstrates the main implementation issue of the DDM. The large amount of zero value estimates influences the statistics of those models and thus their performances significantly. Therefore, a sample including only non-zero value estimates of all models will be analyzed in the later sensitivity analysis.

The cost of equity which is assumed to represent the appropriate discount rate for the three FBVMs is calculated using the capital asset pricing model (CAPM) (Francis, Olsson et al. 2000):

$$r_e = r_f + \beta \times [E(r_m) - r_f] \tag{19}$$

where

r_e	Firm and time specific cost of equity
r_f	Time specific risk-free rate
β	Time specific measure of systematic risk
$E(r_m)$-r_f	Market risk premium

CRSP reports firm specific annual betas calculated using monthly firm returns and the value-weighted return index for the aggregate market. However, Fama and French (1997) propose that firm specific costs of equity are less precise than those for industries. Hence, the median beta of each industry – classified by the first two digits of the SIC – is used to calculate an industry costs of equity for each firm observation. As suggested by Penman and Sougiannis (1998) the three-year U.S.-treasury bond yield at the end of the fiscal year is used as a risk-free rate and a market risk premium of 6% is applied. The results are robust to altering the risk-free rate to a ten-year U.S.-treasury bond yield or the market risk premium to 5%. The DDM can then be performed using analyst consensus forecasts of dividends for the next two years:

$$V_i^{DDM} = \frac{DPS1_i}{1+r_e} + \frac{DPS2_i}{(1+r_e)^2} + \frac{\frac{DPS2_i \times (1+0.0174)}{r_e - 0.0174}}{(1+r_e)^2} \tag{20}$$

where

V_i^{DDM}	Value estimate using a DDM
$DPS1_i$	Analyst consensus one year ahead forecasts of dividends per share
$DPS2_i$	Analyst consensus two year ahead forecasts of dividends per share

The DFCFM requires expected FCFEs for the next two years as input. However, neither *Compustat* provides historical nor *I/E/B/S* forecasted FCFE numbers. Hence, FCFE is calculated as in equation (6) using the provided data of NI, Capex, and D&A. The change in WC and BVD is calculated as followed:

$$\Delta WC_T = WC_t - WC_{t-1} \tag{21}$$

$$WC_t = CA_t - (CL_t - debt\ in\ CL_t) \tag{22}$$

$$\Delta BVD_T = BVD_t - BVD_{t-1} \tag{23}$$

$$BVD_t = TA_t - BVE_t - CL_t + debt\ in\ CL_t \tag{24}$$

where

ΔWC_t	Change in working capital during period T
WC_t	Working capital at time t
CA_t	Current assets at time t
CL_t	Current liabilities at time t
ΔBVD_t	Change in book value of debt during period T
BVD_t	Book value of debt at time t
TA_t	Total assets at time t
BVE_t	Book value of equity at time t

Since no prior observation is available for the first observations (e.g. in 2005), the changes in WC and BVD are set equal to the mean of those changes for that firm. The total FCFEs are then calculated on a per share basis:

$$FCFEPS_i = \frac{FCFE_i}{\text{common shares outstanding}_i \times \text{adjustment factor}_i} \tag{25}$$

Where

$FCFEPS_i$	Free cash flow to equity per share during period t
$FCFE_i$	Free cash flow to equity during period t

and the adjustment factor adjusts for stock splits and stock dividends.

Since no analyst forecasts are available, it is assumed that FCFEPS can be forecasted perfectly, meaning the expected value is equal to the actual value in one (two or three) year(s):

$$FCFEPS1_t = FCFEPS_{t+1} \tag{26}$$

Whenever no future number is available (e.g. in 2015) it is assumed that FCFEPS will grow at the perpetuity growth rate of g=1.74% per annum. The DCFCM can then be performed:

$$V_i^{DCFCM} = \frac{FCFEPS1_i}{1+r_e} + \frac{FCFEPS2_i}{(1+r_e)^2} + \frac{\frac{FCFEPS2_i \times (1+0.0174)}{r_e - 0.0174}}{(1+r_e)^2} \tag{27}$$

where

V_i^{DCFCM}	Value estimate using a DCFCM

For the RIVM, BVEPS at the beginning of the forecast period can be calculated:

$$BVEPS_i = \frac{total\ ordinary\ equity_i}{\text{common shares outstanding}_i \times \text{adjustment factor}_i} \tag{28}$$

Future BVEPS is calculated using the CSR and assuming a constant dividend payout ratio represented as dividends divided by NI at the beginning of the forecasting period. Dividend payout ratios exceeding one are set equal to one assuming that a firm cannot distribute more than it generates to survive in the long run. Additionally, negative payout ratios are set equal to zero since a firm is not able to distribute negative capital. Then, the RIVM is calculated:

$$V_i^{RIVM} = \text{BVEPS}_i + \frac{RI1_i}{1+r_e} + \frac{RI2_i}{(1+r_e)^2} + \frac{\frac{RI2_i \times (1+0.0174)}{r_e - 0.0174}}{(1+r_e)^2} \tag{29}$$

Where

V_i^{RIVM}	Value estimate using a RIVM
$RI1_i$	$EPS1_i$ - $BVEPS_i \times r_e$
$RI2_i$	$EPS1_i$ - $r_e \times (BVEPS_i + EPS1_i \times (1\text{-}dpr_i))$
dpr_i	Dividend payout ratio

Moving on to the MBVM, based on the research of Liu, Nissim et al. (2002) analyst consensus one year ahead earnings forecasts are used as a value driver. Following the suggestion of Baker and Ruback (1999), the benchmark multiple is calculated as the harmonic mean of the two-digit SIC code peer group excluding the target firm. The results are robust to changes to median benchmark multiples or three-digit SIC classification. Finally, the benchmark multiple is multiplied with the firm specific value driver to calculate the value estimate:

$$V_i^{PE1} = EPS1_i \times \frac{n}{\sum \frac{EPS1_j}{Prc4_j}} \tag{30}$$

where

V_i^{PE1}	Value estimate using a PE1
$EPS1_i$	Analyst consensus one year ahead forecasts of earnings per share
$Prc4_j$	Observed share price of the j^{th} comparable firm at the end of four months after fiscal year ends
n	Number of comparable firms

3.2 Empirical results

3.2.1 Main findings

Table 2 shows descriptive statistics of Prc4 and value estimates for the four chosen models. Mean and especially median of DDM estimates are very low compared to Prc4 indicating an underestimation for this model. However, DDM is largely affected by the number of zero-value estimates. DFCFM shows a large dispersion between mean and median also caused among others by the zero-value estimates. RIVM and PE1 seem to generate similar and the most accurate value estimates regarding mean and median.

Table 2

Descriptive Statistics of value estimates and share price[1]

	Obs.	Mean	Std. Dev.	Q1	Median	Q3
Prc4	11,572	41.47	33.71	18.40	33.13	54.30
PE1	11,572	37.53	35.11	14.02	27.99	49.36
DDM	11,572	9.39	15.20	0.00	3.00	12.27
DFCFM	11,572	48.62	88.57	1.16	17.65	56.50
RIVM	11,572	39.17	38.28	14.65	27.30	50.00

[1] Descriptive statistics including number of observations (Obs.) over the total observation period from 2005 to 2015, mean, standard deviation (Std. Dev.), first quartile (Q1), median, and third quartile (Q3) for stock prices at the end of four month after fiscal year ends (Prc4) and the value estimates of the four chosen models PE1, DDM, DCFCM, as well as RIVM all for the total sample are presented.

To evaluate the estimates in more detail, signed valuation errors (SVEs) and absolute prediction errors (APEs) both scaled by stock price are calculated:

$$SVE_i^M = \frac{V_i^M - Prc4_i}{Prc4_i} \tag{31}$$

$$APE_i^M = \frac{|V_i^M - Prc4_i|}{Prc4_i} \tag{32}$$

where

SVE_i^M	Scaled signed valuation error of observation *i* using the model M=DDM, DCFCM, RIVM, or PE1
APE_i^M	Scaled absolute prediction error of observation *i* using the model M=DDM, DCFCM, RIVM, or PE1
V_i^M	Value estimate observation *i* using the model M=DDM, DCFCM, RIVM, or PE1
$Prc4_i$	Observed share price at the end of four months after fiscal year ends

SVEs explain the first evaluation level – bias. Considering mean and median SVEs, positive and negative values may offset each other. Hence, this gives an indication whether a valuation model leads on average to an over- or underestimation. Penman and Sougiannis (1998) focus on this performance metrics as they analyze the market using a portfolio approach. In that case, the net deviation from market prices is of high interest. However, this dissertation uses firm specific market prices and value estimates. To evaluate how close value estimates are to market prices APEs are considered as they only take absolute differences into account. Hence, APEs explain the second evaluation level – accuracy.

T-tests for means and Wilcoxon signed-rank tests for medians are used for statistical inference of SVEs and APEs. While t-tests follow an parametric approach meaning they assume a certain population distribution, the Wilcoxon signed-rank test is of non-parametric nature and does not make such an assumption (Anderson 2017). To evaluate if value estimates are biased, SVEs are tested on the equality to zero:

$$H_0: mean/median\ SVE\ = 0$$

$$H_1: mean/median\ SVE \neq 0$$

To analyze and to compare the accuracy of the different models, APEs are tested on equality:

$$H_0: mean/median\ APE\ of different\ models\ are\ equal$$

$$H_1: mean/median\ APE\ of\ different\ models\ are\ not\ equal$$

Panel 1 of table 3 depicts mean and median SVEs with p-values of t-tests and Wilcoxon signed-rank tests on the equality to zero in parentheses. Panel 2 of table 3 shows mean and median

APEs and p-values of t-tests and Wilcoxon signed-rank tests on the equality of the different models. The chosen significance level in this dissertation is 5%.

All SVEs are significantly different from zero suggested by p-values smaller than 0.05. Regarding the median SVEs, all models underestimate the firm value. However, on average only the DDM leads to an underestimation suggesting that large overestimations by the other three models lead to positive SVEs. Regarding accuracy, PE1 performs best, followed by RIVM, DCFCM, and DDM. Both mean and median APEs are smallest for PE1 while p-values of 0.00 suggest that those are different for all four models. This result contradicts the developed hypothesis as this indicates that a MBVM is more accurate than all three FBVMs. Nevertheless, within the group of FBVMs, RIVM is the most accurate as expected.

Table 3

Prediction Errors

Panel A: Signed Valuation Errors[1]

Value Estimate	Mean	p-values	Median	p-values
PE1	0.03	0.01	-0.10	0.00
DDM	-0.73	0.00	-0.90	0.00
DCFCM	0.30	0.00	-0.45	0.00
RIVM	0.14	0.00	-0.13	0.00

Panel B: Absolute Prediction Errors[2]

Value Estimate	Mean	Versus DDM	Versus DCFCM	Versus RIVM	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.47	0.00	0.00	0.00	0.30	0.00	0.00	0.00
DDM	0.83		0.00	0.00	0.91		0.00	0.00
DCFCM	1.25			0.00	0.85			0.00
RIVM	0.57				0.33			

[1] Panel A reports mean and median signed valuation errors for the total sample as well as p-values of t-tests for means and Wilcoxon signed-rank tests for medians comparing the signed valuation errors to zero.

[2] Panel B reports mean and median absolute prediction errors for the total sample. P-values of t-tests comparing means of the respective row-column combination are displayed in columns three to five. P-values of Wilcoxon signed-rank tests comparing medians of the respective row-column combination are presented in columns seven to nine.

To evaluate this result in more depth, OLS regressions are run to determine whether the different value estimates can explain variation in stock prices. Panel A in table 3 reports results of four univariate regressions of Prc4 on the four different value estimates, respectively. The coefficients of all regressions as well as the constants are statistically significant indicated by a p-value of 0.00. Given the presence of heteroscedasticity in all four regressions[4], robust standard errors are presented.

Table 4

Results of Regressions of Stock Prices on Intrinsic Value Estimates

Panel A: Univariate Regressions of Price on Value Estimate[1]

		OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
PE1	β	0.69 (0.00)	0.01	-22.67	11,572	0.52
	Constant	15.44 (0.00)	0.46			
DDM	β	0.67 (0.00)	0.03	-12.65	11,572	0.09
	Constant	35.18 (0.00)	0.36			
DCFCM	β	0.14 (0.00)	0.01	-126.02	11,572	0.14
	Constant	34.62 (0.00)	0.36			
RIVM	β	0.59 (0.00)	0.01	-30.98	11,572	0.45
	Constant	18.33 (0.00)	0.45			

Panel B: Multivariate Regression of Price on Value Estimates of PE1 and RIVM[2]

	OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
β_{PE1}	0.52 (0.00)	0.02	-22.32	11,572	0.53
β_{RIVM}	0.19 (0.00)	0.02	-43.61		
Constant	14.59 (0.00)	0.45			

[1] Panel A reports regression results of following univariate regression: $Prc4_i = \alpha + \beta V_i^M + \varepsilon_i$ where α is a constant, V_i^M is the value estimate for observation *i* using the Model *M* = DDM, DFCFM, RIVM, or PE1 and ε_i is a residual. White adjusted p-values in parentheses and standard errors (Robust Std. Err.) are reported in order to overcome a heteroscedasticity issue. T-statistics testing the OLS coefficient on the equality to 1 are presented in the fifth column.

[2] Panel B reports regression results of following multivariate regression $Prc4_i = \alpha + \beta_{PE1} V_i^{PE1} + \beta_{RIVM} V_i^{RIVM} + \varepsilon_i$ where α is a constant, V_i^{PE1} is the value estimate for observation *i* using the PE1 model, V_i^{RIVM} is the value estimate for observation *i* using the RIVM, and ε_i is a residual. White adjusted p-values in parentheses and standard errors (Robust Std. Err.) are reported in order to overcome a heteroscedasticity issue. T-statistics testing the OLS coefficient on the equality to 1 are presented in the fifth column.

A positive and significant constant in each regression indicates an underestimation by all four models. Furthermore, testing the OLS coefficients on the equality to 1 suggests that none of the four models is perfectly linear linked to Prc4 indicated by t-statistics larger than the critical value of 1.96[5]. The R-squared is an indicator of explainability (Wooldridge 2016) and is largest

[4] A white test is performed for each model, respectively, indicating the presence of heteroscedasticity with a p-value of 0.00.

[5] Significance level of 5%.

for the PE1 followed by RIVM, DCFCM, and DDM. A little bit more than half of the variability in Prc4 can be explained by the intrinsic value estimate of PE1. While RIVM explains a little bit less with 45%, DCFCM and DDM explain only 14% and 9%, respectively. Those results underline the outperformance of PE1 over the three FBVMs. However, RIVM performs nearly as good as PE1 and outperforms DCFCM and DDM significantly.

The two best performing models, PE1 and RIVM, are compared in a multivariate regression. Panel B in table 4 shows results for this multivariate regression including Prc4 as dependent variable and RIVM as well as PE1 estimates as regressors. Including the RIVM estimate as explanatory variable only adds 1% to the R-squared. Hence, RIVM can only capture a small amount of additional information compared to PE1.

Since the first hypothesis is found to be wrong, the assumptions and implementation issues for the FBVMs may create larger errors than the dependence on comparable firms for the PE1. Furthermore, using market prices as a direct input factor for PE1 might lead to intrinsic value estimates closer to observed market prices. One possible explanation for those findings is that MBVMs find prices representing the current mood of the market whereas FBVMs find values based on a perfect market and specific conditions as described by Schreiner and Spremann (2007). However, in line with prior research and as hypothesized RIVM performs better than the other two FBVMs (Penman and Sougiannis 1998, Francis, Olsson et al. 2000). Since FBVMs receive great attention, this outperformance will be analyzed as a next step.

3.2.2 Comparison of FBVMs

Since DCFCM and DDM resulted in many zero-value estimates, in this part a sample of 5,997 observations including only non-zero value estimates is considered in order to come to less biased results. Francis, Olsson et al. (2000) argue that a lower portion of TV and the inclusion of BVEPS as stock component is one reason for the outperformance of RIVM. On average BVEPS accounts for 34.58% of the RIVM value estimate while TV makes up 59.22%. TV accounts for 89.79% (89.52%) in DCFCM (DDM) on average and hence, the estimate depends way more on the TV. Thus, their argument might be true and errors in forecasting, growth assumptions, as well as risk adjustments have a larger influence on estimates of DDM and DCFCM. For further analysis, the sample is split into a low TV (LTV) and a high TV (HTV) group using the first quartile and fourth quartile of TVs as breakpoints.

Table 5

Analysis of influence of terminal value on value estimate

Panel A: Comparison of absolute prediction errors[1]

	DDM			DCFCM			RIVM		
	Total	LTV	HTV	Total	LTV	HTV	Total	LTV	HTV
Median value estimate	10.06	2.48	34.41	33.97	5.07	128.89	33.88	13.69	85.18
Median absolute prediction error	0.75	0.92	0.48 (0.00)	0.64	0.83	1.36 (0.00)	0.31	0.37	0.34 (0.01)

Panel B: Univariate Regressions of absolute prediction errors on model components[2]

		OLS Coefficient	Robust Std. Err.	Model Obs.	R^2
DDM	β_{TV}	-0.00 (0.00)	0.00	5,997	0.01
	Constant	0.76 (0.00)	0.01		
DCFCM	β_{TV}	0.02 (0.00)	0.00	5,997	0.34
	Constant	0.19 (0.00)	0.06		
RIVM	β_{TV}	0.01 (0.00)	0.00	5,997	0.08
	Constant	0.24 (0.00)	0.03		

[1] The sample of 5,997 observations which includes only positive value estimates is split into low terminal value (LTV) and high terminal value (HTV) groups using first and fourth quartile as breakpoints. Median value estimates and median absolute prediction errors are presented for the total sample, LTV as well as HTV groups for each model, respectively. In columns 4, 7, and 10 p-values of two-sample Wilcoxon rank-sum tests on the equality of medians of the LTV and HTV are presented in parentheses.

[2] Results of following regressions are reported: $APE_i^M = \alpha + \beta_{TV} V_{TV,i}^M + \varepsilon_i$ where APE_i^M is the absolute prediction error of model M=DDM, DCFCM, or RIVM, $V_{TV,i}^M$ is the present value of terminal value calculated at the end of the forecast horizon and ε_i is a residual all of observation *i*. White adjusted p-values in parentheses and robust standard errors (Robust Std. Err.) are reported in order to overcome a heteroscedasticity issue.

Panel A of table 5 presents median value estimates and APEs of the FBVMs for the total sample as well as the LTV and HTV groups. Median APEs are different for the LTV and HTV groups for all three models indicated by p-values of less than 0.05. However, while accuracy of DCFCM decreases significantly from the LTV (0.83) group to the HTV group (1.36), it even improves for the RIVM (0.37 to 0.34) indicating that TV is one reason for the outperformance of RIVM over DCFCM. Accuracy of DDM improves a lot for the HTV group (0.48) compared to the LTV (0.92). This result is however misleading because DDM value estimates are strongly negatively biased. Although a higher TV increases the median value estimate from 2.48 (LTV) to 34.41 (HTV) and improves accuracy, it still underestimates the median Prc4 of 40.28. Panel B of table 5 reports results of three univariate regressions of APEs on the TV of respective models. The TV of DDM and RIVM can only explain 2% (DDM) and 8% (RIVM) of the variability of APEs. An R-squared of 34% indicates that DCFCM´s TV explains more variability of APEs which underlines the impact of TV on the value estimates of DCFCM while the other two models are not as affected. However, for the DDM the underestimation issue must be kept in mind.

3.2.3 Effect of Research and Development expenses

Francis, Olsson et al. (2000) argue that if BVEPS cannot capture all relevant assets, RIVM still outperforms since larger RI in the future is linked with lower BVEPS today. To analyze this, they split their sample in firms with low and high R&D. As a next step, this analysis is replicated for the entire sample of 11,572 firm observations. The low R&D group includes all firms that do not report R&D totaling to 5,602 observations. The high R&D group includes the fourth quartile of firm observations based on the ratio of R&D to TA of the beginning of the fiscal year amounting to 2,166 firm observations.

Panel A of table 6 reports median APEs for both subsamples, low and high R&D, as well as p-values of Wilcoxon signed-rank tests comparing the different models and rank-sum tests comparing model performance between the two subsamples. P-values of zero indicate that the accuracy of all models is significantly different. In line with the previous results, PE1 is most accurate in both subsamples followed by RIVM. Moreover, p-values larger than 0.05 suggest that the accuracy of PE1 (0.17) and RIVM (0.56) does not significantly change for the two-subsamples. This supports the hypothesis made by Francis, Olsson et al. (2000) that RIVM outperforms other FBVMs also in high R&D groups. Regarding DDM and DCFCM the accuracy changes significantly for the two subsamples indicated by p-values of 0.00. While DDM is more accurate in the low R&D group and outperforms DCFCM in that subsample, the result is opposite in the high R&D group. Panel B reports OLS regression results. Since the explainability measured by R-squared is larger for the RIVM in the high R&D group than in the low R&D group, there is evidence that RIVM performs even better in high R&D group. Only the R-squared for the PE1 regressions is larger in the low R&D group indicating that PE1 performs better in that group. Additionally, R-squared in the high R&D group is 52% for both PE1 and RIVM underlining the increased accuracy of RIVM for that subsample.

Table 6
Analysis of influence of R&D on value estimate

Panel A: Absolute Prediction Errors[1]

	Low R&D				High R&D			
Model	Median	Versus DDM	Versus DCFCM	Versus RIVM	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.30	0.00	0.00	0.00	0.28 (0.17)	0.00	0.00	0.00
DDM	0.88		0.00	0.00	1.00 (0.00)		0.00	0.00
DCFCM	0.92			0.00	0.74 (0.00)			0.00
RIVM	0.31				0.31 (0.56)			

Panel B: Univariate regressions of Price on Value estimate[2]

			OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
Low R&D	PE1	β	0.75 (0.00)	0.02	-13.17	4,197	0.57
		Constant	13.25 (0.00)	0.62			
	DDM	β	0.45 (0.00)	0.04	-13.81	4,197	0.05
		Constant	35.91 (0.00)	0.62			
	DCFCM	β	0.12 (0.00)	0.01	-85.29	4,197	0.11
		Constant	34.76 (0.00)	0.58			
	RIVM	β	0.60 (0.00)	0.02	-19.36	4,197	0.47
		Constant	16.30 (0.00)	0.73			
High R&D	PE1	β	0.70 (0.00)	0.03	-11.75	2,166	0.52
		Constant	18.20 (0.00)	1.00			
	DDM	β	0.97 (0.00)	0.08	-0.42	2,166	0.09
		Constant	39.77 (0.00)	1.02			
	DCFCM	β	0.23 (0.00)	0.02	-48.07	2,166	0.22
		Constant	35.66 (0.00)	0.89			
	RIVM	β	0.68 (0.00)	0.03	-11.78	2,166	0.52
		Constant	19.24 (0.00)	0.98			

[1] Panel A reports median absolute prediction errors for the low and high R&D groups. P-values of Wilcoxon signed-ranked tests comparing medians of the respective row-column combination are presented in columns three to five and seven to nine. P-values of two-sample Wilcoxon rank-sum tests on the equality of medians of low and high R&D groups are presented in parentheses in column six.

[2] For description of performed regressions look at table 4 panel A. Those regressions are performed for low and high R&D groups separately.

3.2.4 Sensitivity Analysis

In this section different key assumptions for the different models are altered to evaluate whether the above described results are robust to changes or not.

3.2.4.1 Cost of equity

The risk-free rate is altered to a ten-year US-treasury bond yield and the market risk premium is changed to 5%, respectively. Results are shown in Table 7. Both alternatives change accuracy slightly for the FBVMs. While DDM performs slightly more accurate in both cases, RIVM´s APEs are minimal lower using a ten-year risk-free rate. DCFCM performs less accurate in both cases. The ranking of accuracy between the four models does not change. However, DDM and DCFCM do not perform significantly different from each other using a ten-year rate indicated by a p-value of 0.79. Explainability decreases in both cases for each model.

Table 7

Sensitivity analysis of changes in the cost of equity

Panel A: Absolute Prediction Errors[1]

	10-year risk-free rate				5% market risk premium			
Model	Median	Versus DDM	Versus DCFCM	Versus RIVM	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.30	0.00	0.00	0.00	0.30	0.00	0.00	0.00
DDM	0.90		0.79	0.00	0.90		0.00	0.00
	(0.00)				(0.00)			
DCFCM	0.87			0.00	0.91			0.00
	(0.00)				(0.00)			
RIVM	0.33				0.36			
	(0.01)				(0.00)			

Panel B: Univariate regressions of Price on Value estimate[2]

			OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
10-year risk-free rate	DDM	β	0.58 (0.00)	0.02	-18.37	11,572	0.09
		Constant	35.34 (0.00)	0.36			
	DCFCM	β	0.12 (0.00)	0.01	-132.04	11,572	0.13
		Constant	35.12 (0.00)	0.39			
	RIVM	β	0.50 (0.00)	0.01	-39.07	11,572	0.43
		Constant	19.74 (0.00)	0.49			
5% market risk premium	DDM	β	0.53 (0.00)	0.02	-22.51	11,572	0.09
		Constant	35.30 (0.00)	0.36			
	DCFCM	β	0.11 (0.00)	0.01	-159.05	11,572	0.13
		Constant	34.83 (0.00)	0.36			
	RIVM	β	0.46 (0.00)	0.01	-52.01	11,572	0.44
		Constant	19.23 (0.00)	0.44			

[1] Panel A reports median absolute prediction errors for the total sample. Columns two to five present results using a ten-year US-treasury bond yield as a risk-free rate and a 6% market risk premium. Columns six to nine present results using a three-year US-treasury bond yield as a risk-free rate and a 5% market risk premium. P-values of Wilcoxon signed-rank tests comparing medians to the base case using a three-year risk-free rate and a 6% market risk premium are presented in parentheses. P-values of Wilcoxon signed-rank tests comparing medians of the respective row-column combination are presented in columns three to five and seven to nine.

[2] For description of performed regressions look at table 4 panel A.

3.2.4.2 Forecast horizon

The forecast horizon is expanded to three-years[6] and results are reported in table 8. Since less analyst consensus forecasts are available for three-year ahead EPS and DPS, the sample is reduced to 8,728 observations. The accuracy does not significantly change for the RIVM indicated by a p-value of 0.05. A p-value of 0.16 suggests that accuracy of DDM and DCFCM is not significantly different if a three-year forecast horizon is used. Overall, PE1 performs still best followed by RIVM. Explainability does not change a lot for all models if compared using the same sample. Hence, expanding the forecast horizon cannot significantly improve the performance of FBVMs.

Table 8

Sensitivity analysis of changes in the forecast horizon

Panel A: Absolute Prediction Errors[1]

	Three-year forecast horizon			
Model	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.29	0.00	0.00	0.00
DDM	0.90 (0.00)		0.16	0.00
DCFCM	0.85 (0.01)			0.00
RIVM	0.33 (0.05)			

Panel B: Univariate regressions of Price on Value estimate using a three-year forecast horizon[2]

		OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
PE1	β	0.70 (0.00)	0.01	-21.04	8,728	0.53
	Constant	16.11 (0.00)	0.51			
DDM	β	0.58 (0.00)	0.03	-15.24	8,728	0.08
	Constant	37.97 (0.00)	0.44			
DCFCM	β	0.13 (0.00)	0.01	-124.72	8,728	0.13
	Constant	36.88 (0.00)	0.43			
RIVM	β	0.57 (0.00)	0.01	-29.77	8,728	0.45
	Constant	18.99 (0.00)	0.57			

[1] Panel A reports median absolute prediction errors using a three-year forecast horizon. P-values of Wilcoxon signed-rank tests comparing medians to the base case using a two-year forecast horizon are presented in parentheses. P-values of Wilcoxon signed-rank tests comparing medians of the respective row-column combination are presented in columns three to five. Sample size is reduced to 8,728 observations as less observations of three-year ahead analyst consensus forecasts are available. Three-year FCFE forecasts are calculated using the same assumptions as for the calculations of FCFE1 and FCFE2.

[2] For description of performed regressions look at table 4 panel A. Sample includes only 8,728 observations and a three-year forecast horizon is used.

[6] This might improve performance of FBVMs as the portion of TV should be reduced.

3.2.4.3 Long-term growth rate

The long-term growth rate is altered to *g*=4% and *g*=0% similar to the analysis by Francis, Olsson et al. (2000) and Penman and Sougiannis (1998). Results are shown in Table 9 reports results. While accuracy remains similar in the no-growth case, accuracy significantly decreases in the 4% growth case. However, RIVM still performs second most accurate in both cases but DCFCM performs less accurate than DDM in the 4% growth case. Explainability increases for all FBVMs in the no-growth case but decreases substantially for the 4% growth case. Thus, the assumption made in the base case leads to better value estimates than using a 4% growth rate. Performance ranking remains in both cases mainly the same suggesting that the results are robust to this alteration.

Table 9

Sensitivity analysis of changes in the long-term growth rate

Panel A: Absolute Prediction Errors[1]

	g=0%				*g*=4%			
Model	Median	Versus DDM	Versus DCFCM	Versus RIVM	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.30	0.00	0.00	0.00	0.30	0.00	0.00	0.00
DDM	0.92		0.00	0.00	0.92		0.00	0.00
	(0.00)				(0.00)			
DCFCM	0.80			0.00	0.99			0.00
	(0.00)				(0.00)			
RIVM	0.33				0.42			
	(0.01)				(0.00)			

Panel B: Univariate regressions of Price on Value estimate[2]

			OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
g=0%	DDM	β	0.93 (0.00)	0.04	-2.07	11,572	0.10
		Constant	34.77 (0.00)	0.37			
	DCFCM	β	0.20 (0.00)	0.01	94.44	11,572	0.15
		Constant	34.03 (0.00)	0.35			
	RIVM	β	0.77 (0.00)	0.02	-14.48	11,572	0.48
		Constant	15.65 (0.00)	0.45			
g=4%	DDM	β	0.17 (0.00)	0.01	-95.60	11,572	0.05
		Constant	38.35 (0.00)	0.33			
	DCFCM	β	0.03 (0.00)	0.00	-219.45	11,572	0.06
		Constant	38.38 (0.00)	0.45			
	RIVM	β	0.14 (0.00)	0.01	-112.46	11,572	0.20
		Constant	32.18 (0.00)	0.46			

[1] For description of panel A see table 7 panel A. Reported statistics are the same. Calculations are based on two different cases using a long-term growth of *g*=0% and *g*=4% for TV calculations.

[2] For description of panel B see table 4 panel A.

3.2.4.4 Comparable firms and benchmark multiples

For the chosen MBVM, PE1, the key assumptions regarding the choice of comparable firms and the calculation method for the benchmark multiple are altered. First, the benchmark multiple is calculated using the median and the arithmetic mean instead of harmonic mean. Second, the benchmark multiple is calculated using the harmonic mean but identifying comparable firms by using the first three digits of SIC, which Alford (1992) argues should increase accuracy. Using the three-digit SIC reduces the sample by 4,525 observations as only observations with at least ten comparable firms are considered.

Table 10

Sensitivity analysis of changes in the choice of benchmark multiple and comparable firms

Panel A: Absolute Prediction Errors[1]

	Harmonic Mean		Median		Mean		SIC3	
Model	Median	Versus RIVM	Median	Versus RIVM	Median	Versus RIVM	Median	Versus RIVM
PE1	0.32	0.00	0.30 (0.01)	0.00	0.57 (0.00)	0.00	0.33 (0.00)	0.00
RIVM	0.35							

Panel B: Univariate regressions of Price on Value estimate[2]

	Model		OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
Harmonic mean	PE1	β	0.69 (0.00)	0.01	-3.91	7,047	0.52
		Constant	15.48 (0.00)	0.40			
Median	PE1	β	0.62 (0.00)	0.01	-51.60	7,047	0.50
		Constant	15.16 (0.00)	0.42			
Mean	PE1	β	0.33(0.00)	0.00	-151.75	7,047	0.44
		Constant	19.40 (0.00)	0.42			
SIC3	PE1	β	0.67 (0.00)	0.02	-44.05	7,047	0.52
		Constant	15.86 (0.00)	0.56			
	RIVM	β	0.61 (0.00)	0.01	-51.25	7,047	0.48
		Constant	17.27 (0.00)	0.41			

[1] Sample is reduced by 4,525 observations since only observations with at least ten comparable firms are considered leaving a sample of 7,047 observations.

[2] Panel A reports median absolute prediction errors of PE1 using the harmonic mean, median and arithmetic mean of comparable firms as benchmark multiple and the first two digits of SIC for comparable firms as well as using the harmonic mean but classifying comparable firms by the first three digits of SIC (SIC3). P-values of Wilcoxon signed-rank tests comparing medians to the base case the harmonic mean and two-digit SIC comparable firms are presented in parentheses. P-values of Wilcoxon signed-rank tests comparing medians to RIVM absolute prediction errors are presented in column three, five, seven, and nine.

[3] For description of panel B see table 4 panel A.

Table 10 reports results of accuracy and explainability for all three cases. While using the median for calculation improves accuracy (0.30 vs. 0.28) it reduces explainability (0.50 vs. 0.52). Using the first-three digit SIC does neither improve accuracy (0.33 vs. 0.32) nor explainability (0.52 vs. 0.52). In both cases, PE1 still outperforms RIVM. Using the arithmetic mean reduces accuracy and explainability significantly. In that case, PE1 no longer outperforms RIVM.

3.2.4.5 Consideration of positive value estimates

As mentioned earlier, DDM and DCFCM contain many zero-value estimates. Excluding those reduces the sample size to 5,997. Table 11 reports results including only positive value estimates. Although accuracy of DDM and DCFCM in this sample improves, DDM is still the least accurate followed by DCFCM, RIVM and PE1. Regarding explainability, PE1 still outperforms all FBVMs and RIVM performs best within FBVMs. However, DDM now explains more variability in Prc4 than DCFCM.

Table 11[1]

Analysis only including positive value estimates

Panel A: Absolute Prediction Errors[2]

Model	Median	Versus DDM	Versus DCFCM	Versus RIVM
PE1	0.25	0.00	0.00	0.00
DDM	0.75		0.02	0.00
DCFCM	0.64			0.00
RIVM	0.31			

Panel B: Univariate regressions of Price on Value estimate using a three-year forecast horizon[3]

		OLS Coefficient	Robust Std. Err.	t-statistic OLS Coefficient = 1	Model Obs.	R^2
PE1	β	0.70 (0.00)	0.01	-18.64	5,997	0.57
	Constant	16.11 (0.00)	0.51			
DDM	β	0.71 (0.00)	0.03	-9.04	5,997	0.14
	Constant	36.04 (0.00)	0.54			
DCFCM	β	0.13 (0.00)	0.01	-113.04	5,997	0.13
	Constant	39.35 (0.00)	0.52			
RIVM	β	0.55 (0.00)	0.02	-26.47	5,997	0.45
	Constant	22.53 (0.00)	0.69			

[1] Sample includes only positive value estimates leaving 5,997 observations.

[2] For description of panel A see table 3 panel B. Only medians are reported.

[3] For description of panel B see table 4 panel A.

3.3 Conclusion and limitations

The described findings suggest that a MBVM using forecasted earnings results in more accurate value estimates and higher explainability than FBVMs which contradicts the first hypothesis. However, within the group of FBVMs a RIVM performs best which is in line with the second hypothesis.

Key findings may be limited given the sample selection process and thus, might not be representative for firm valuations not following the criteria of sample selection. Furthermore, DCFCM follows many assumptions starting with the calculation of FCFE, assuming a perfect forecast, and applying the equity method. However, using analyst consensus forecasts of FCFE or applying the entity method may increase the performance. Analyzing the performance in different industry groups or using different value drovers for MBVMs could supplement this dissertation. Moreover, the financial crisis 2008 lies within the observation period and may cause distortion in share prices and hence, valuation errors. The effect of the financial crisis on stock valuation may be an interesting research topic which should be further analyzed.

4 Case Study

Although in theory, the different valuation models result in the same value estimate, the LSA could reveal superior performance of the PE1 model over FBVMs and an outperformance of RIVM within the group of FBVM. However, given the importance in practice of some of those models, it is questioned which of those models and how those are applied by financial analysts. In this case study, three sell-side equity analysts´ reports of a company are examined to answer this question exemplary. First, the key elements of an analyst report are described and previous research on this topic is reviewed. Afterwards, three reports are analyzed as an example.

4.1 Analyst reports

Sell-side equity analysts gather information about a company in order to evaluate its future performance (Asquith, Mikhail et al. 2005). Based on the collected information they forecast future accounting flows and translate those into a firm valuation (Demirakos, Strong et al. 2010). This value estimate is then used to recommend buying, holding, or selling the stock of the firm. Thus, an analyst report usually contains earnings forecasts, a value estimate – also known as target price – a stock recommendation, and explanations as well as justifications (Asquith, Mikhail et al. 2005, Demirakos, Strong et al. 2010, De Franco, Hope et al. 2015). Those reports receive interest especially by investors such as fund managers, which represent a major client of sell-side analysts (Imam, Barker et al. 2008).

Although some might argue that such analyst reports are only a collection of pre-existing information, Asquith, Mikhail et al. (2005) discovered in an event study analyzing analyst report releases and corresponding price reactions that analyst recommendations contain new information and security prices react on forecast or recommendation revisions. Moreover, they found that the stronger the given justification for a recommendation is the stronger is the market´s reaction.

4.2 The Use of valuation models by sell-side equity analysts

In the process of valuing a firm, sell-side equity analysts make use of different valuation models including MBVMs and FBVMs. After research has focused on the theoretical relative performance of different models (e.g. Francis, Olsson et al. 2000, Liu, Nissim et al. 2002), the interest in which models and how those are used by analysts in practice has risen (e.g. Demirakos, Strong et al. 2004, Imam, Barker et al. 2008)

Demirakos, Strong et al. (2004) analyzed reports about firms from three different industries. They found that the model choice is affected by the industry of a firm given their different characteristics. However, analysts apply mainly MBVMs, in particular PER models, whose use increases in more stable industries. DCFCM is the favored FBVM and RIVM is only rarely used, also discovered by Hand, Coyne et al. (2017). Besides industry group, Demirakos, Strong et al. (2004) found that the acceptability to clients and the familiarity of the analyst with the model are important factors for the model choice, as well. Imam, Barker et al. (2008) see the client´s interest in DCFCMs as a major force leading to an increasing usage of DCFCMs in past years. Nevertheless, they believe that practical implementation issues of DCFCMs such as estimating a discount rate or creating forecasts result in a continued usage of MBVMs as the main valuation technique while DCFCMs only supplement MBVMs to convey information to the clients. Demirakos, Strong et al. (2010) mainly agree with those findings and identified certain situations in which DCFCMs are more popular than MBVMs including high-risk firms, small firms, bull-markets or whenever a limited number of comparable firms is available.

Regarding analysts´ performance measured by the accuracy of target prices, Asquith, Mikhail et al. (2005) found that around half of analyst´s value estimates are met within twelve month. However, no relation between model choice and accuracy was identified. On the contrary, Demirakos, Strong et al. (2010) identified an unconditional outperformance of PER-models over DCFCMs. However, after adjusting for effects of the certain situations in which DCFCMs are applied by analysts, DCFCMs´ performance improves significantly leading to an outperformance over PER-models.

De Franco, Hope et al. (2015) analyze which peer companies are used whenever a MBVM is applied by analysts. They discover that peers with higher valuation are chosen by analysts. Although this might be a justification for optimistic target prices, other factors such as expected similar growth opportunities may be the reason for this biased selection.

4.2.1 Hypothesis Development

The purpose of this case study is to identify which valuation models are used by equity sell-side analysts in practice. Based on the literature discussed in the previous section a hypothesis for this question is developed.

It is often argued, that analysts focus on MBVMs in the valuation process given the simplicity of MBVMs and implementation issues of FBVMs regarding estimating discount rates as well as creating forecasts (Demirakos, Strong et al. 2004, Imam, Barker et al. 2008, Demirakos, Strong et al. 2010). While this may differ in certain situations or industries, MBVMs are especially used in stable industries such as the beverages sector to which the chosen company, which will be analyzed, belongs (Demirakos, Strong et al. 2004, Demirakos, Strong et al. 2010). However, as argued by Imam, Barker et al. (2008) analysts implement valuations based on DFCFMs given their popularity among clients. Other models such as RIVM are rarely applied (Demirakos, Strong et al. 2004). The stable industry of the chosen company, the simplicity of MBVMs but also the increasing popularity of DFCFM among clients lead to following hypothesis:

H1: MBVMs are mainly used for equity valuation by sell-side analysts, sometimes supplemented by a DFCFM

This hypothesis is in line with the findings of the LSA that MBVMs outperform FBVMs. However, the expected use of DFCFMs and the limited existence of RIVMs contradicts with the findings that RIVM performs best among FBVMs.

4.3 Analysis of sell-side equity analyst reports

Three analyst reports by different sell-side equity analysts about the company Dr Pepper Snapple Group, Inc. (DrPS) are analyzed in the following parts to identify which valuation models and how those are applied by practitioners. DrPS is part of the LSA with observations for the fiscal years 2010 to 2015. To ensure a higher topicality and comparability, all three chosen analyst reports are published in October 2015 and contain information regarding the implementation and justification of the chosen valuation method.

4.3.1 Dr Pepper Snapple Group, Inc.

DrPS is a non-alcoholic beverages manufacturer and distributor in the United States, Canada, and Mexico. The company´s product portfolio includes well-known brands such as “Dr Pepper”, “7up”, or “Schweppes” in both of its areas flavored carbonated soft drinks and non-carbonated beverages. Main market for DrPS is North America but specific products are also sold in Europe and Asia (Dr Pepper Snapple Group, Inc., 2016). After a merger in 2018, the company is today known as Keurig Dr Pepper Inc. (Keurig Dr Pepper Inc., 2019). However, this merger does not affect the analysis as the merger was announced and closed in 2018 but the analysis uses data and reports from 2015.

DrPS experiences high competition in the liquid refreshment market with large players such as Coca-Cola and PepsiCo. as major competitors. Taste, price, and brand recognition are only a few of the main areas of competition. Based on retail sales DrPS had a market share of 9% in 2015 in the liquid refreshment market making the company the third largest. However, since DrPS does not only sell packaged beverages but also beverage concentrates many of its competitors are customers, as well (Dr Pepper Snapple Group, Inc. 2016). Table 12 presents DrPS´s key financials over the period 2011 to 2015. After three years of varying sales growth, DrPS stabilized growth in 2014 and 2015 to 2-3%. While sales have slightly grown at low single digit rates, all three key margins – gross profit, EBIT, and NI – have stayed very stable indicating DrPS´s cost discipline. Furthermore, the company was able to slightly improve margins. FCFF, which are important for valuations of later analyzed analyst reports, have been more volatile from 2011 to 2013 and have stabilized around $800m since 2014. To conclude, DrPS´s performance is stable and has improved over the past years. Regarding the capital structure, leverage, calculated by dividing total liabilities by total equity both as book value, has almost not changed over the years and has varied between 2.6 and 3.1. This again indicates the stability of the company. While this stability makes forecasting for analysts less challenging and hence supports the use of FBVMs, it also has positive effects on MBVMs since the relative valuation is unlikely to change exceptionally.

Table 12[1]

Key financials of DrPS over the period 2011 to 2015

	2011	2012	2013	2014	2015
Sales	5,903	5,995	5,997	6,121	6,282
growth	*4.7%*	*1.6%*	*0.0%*	*2.1%*	*2.6%*
Gross Profit	3,418	3,495	3,498	3,630	3,723
margin	*58%*	*58%*	*58%*	*59%*	*59%*
EBIT	1,024	1,092	1,046	1,180	1,298
margin	*17%*	*18%*	*17%*	*19%*	*21%*
Net Income	606	629	624	703	764
margin	*10%*	*11%*	*10%*	*12%*	*12%*
FCFF	542	258	682	851	834
Leverage	3.10	2.92	2.60	2.60	3.06

[1] Table 12 reports key annual financials of DrPS as reported in the annual report for the fiscal years 2011 to 2015. Data was received from the data platform Thomson Reuters. Leverage is calculated by dividing total liabilities by total equity both as book-values at fiscal year-end. Sales, gross profit, EBIT, NI, and FCFF are reported in million U.S. Dollar.

4.3.2 Evercore´s analyst report

The first analyst report by the investment bank Evercore ISI was published on October 4th, 2015 (Metrano, B. and Ottenstein, R., 2015). The analysts changed their recommendation from holding to buying DrPS´s stocks as they believe the company will show a strong performance over the next years for which they name three fundamental reasons. First, they observe the key competitor Coca-Cola facing challenges in emerging markets, which drives the company to increase profits by increasing prices in the U.S. market. The analysts expect PepsiCo. to follow leaving DrPS as a beneficiary since it derives 90% of its sales from the U.S. market. Second, the analysts believe commodity prices will continue to decrease, which should improve DrPS´s gross margin by 1.5% in 2015 since 75% of cost of goods sold are raw material costs. Finally, DrPS launched a strategy program in 2011 (Dr Pepper Snapple Group, Inc. 2016) to save costs and increase profitability. Evercore´s analysts expect further cost savings due to this program over the next years. Besides those three fundamental reasons which all are expected to increase EPS, the analysts see DrPS as a potential acquisition target given its stable financials and relatively small size. They expect a takeover in 2017 to 2018 which could increase the stock price.

Based on the expected market development, the analysts forecast different accounting flows with a focus on EPS and EBITDA. They argue that given the stable and consistent performance of DrPS over the past years in which the company beat eight out of ten EPS quarterly consensus forecasts the company will maintain its current relative valuation. They consider a PER and EV/EBITDA using two-year ahead forecasts of EPS and EBITDA. Thus, they rely only on MBVMs but apply the equity and entity perspective. To set a twelve-month price target, the analysts assume that DrPS´s shares will trade at a PER of 19x and an EV/EBITDA of 12x in twelve months. Nonetheless, they do not exactly state how they came up with the exact multiples but for both multiples, they compare historical numbers of DrPS and its two key competitors Coca-Cola and PepsiCo. A specific averaging technique is not described. Applying the two multiples to the analyst´s estimates results in a target price of $92.00 implying an increase of almost 16%.

4.3.3 RBC´s analyst report

The second report by the British investment bank RBC capital markets was published October 27th, 2015 (Modi, N., et al., 2015). The analysts upgraded the recommendation from sell to hold. They change their negative view given similar fundamental reasons as Evercore´s analysts. However, they use an entity perspective DCFCM for valuation. They forecast revenues and calculate FCFFs using different forecasts and assumptions regarding margins or expenses relative to sales. For this, they split the forecast period into two sub-periods. First, they estimate FCFFs for the next two years using a 2% revenue growth rate. For the eight years after that, they increase the growth rate stepwise to 4% and increase the EBIT margin stepwise to from 21% to 22%. They assume a terminal growth rate of 2%. Using a beta of 0.95, a 10-year U.S. treasury rate of 3% for the first forecast period and of 5% for the second forecast period as a risk-free rate and an equity risk premium of 6% the analysts calculate two costs of equity of 8.7% (first period) and 10.7%. (second period). Using those, a cost of debt of 5% and the respective weights of debt and equity, weighted average costs of capital (WACC) of 6% and 7% are calculated which are used as discount rates for the respective periods. Discounting the estimated FCFFs with the respective WACC over the period from 2015 to 2024 gives an enterprise value. Subtracting net debt leaves the equity value and a target share price of $90.00 which is close to the share price at that time of $89.88.

The target price represents RBC´s base scenario which is expected by the analysts. Additionally, they estimate an upside and a downside scenario in which they assume different terminal growth rates, margins, revenue growth rates and discount rates. With those scenarios the analysts give a range of prices between $62 and $120. Although this range is rather large, it illustrates risk and potential for investors. Since the analysts forecast many accounting variables and use a two-step forecast horizon of in total ten years, they can implement their industry and firm-specific knowledge.

However, although they forecast a longer period, the value estimate still highly depends on the TV which represents approximately 64% of estimated enterprise value. Nevertheless, the analysts do not only rely on the DCFCM. Thus, they calculate the one-year ahead PER implied by their target price and EPS estimate and compare it to the current multiples of comparable firms. They use 20 comparable firms of the same sector including Coca-Cola and PepsiCo. and find that their implied multiple is in line with the industry but rather at the lower end.

Although they derive a similar target price as Evercore´s analysts, they do not recommend buying the stock since the share price has significantly increased in October 2015 and RBC´s analysts believe the fundamental advantages are already reflected in the current price.

4.3.4 Deutsche Bank´s analyst report

The third report by Deutsche Bank was published on October 22nd, 2015 (Alwy, F. and Schmitz, B. Jr, 2015). The analysts do not change the recommendation from hold and only give an update on the current situation. Regarding fundamentals, they see the same drivers as Evercore for the next years. Like RBC they use an entity perspective DCFCM for valuation but combine it with a MBVM. They forecast revenues for the next eight years and calculate FCFFs assuming different margins and expenses relative to sales. They expect a stepwise increasing EBIT margin from 20.8% in 2015 to 23.4% in 2022. Using a 3.5% risk-free rate, a 4% risk premium, and a beta of 0.65 gives a significantly lower cost of equity of 6.1% compared to RBC´s estimate. Using the respective weights of debt and equity as well as the cost of debt gives a WACC of 6.5% which is in line with RBC estimates. They assume a terminal growth rate of 1.5% and base this assumption on the inflation and growth rates of the carbonated soft drink market in the U.S.. Discounting the estimated FCFFs and subtracting net debt leaves a target price of $95 which implies an upside of 12%. As RBC, Deutsche Bank´s analysts argue that most of the fundamental drivers are already reflected in the price given the share price increase in October and hence, only recommend holding the stock. Deutsche Bank´s analysts also face a large dependence on TV which represents approximately 66% of value estimate. The analysts combine the DCFCM with a MBVM using one-year ahead PER and compare it to DrPS´s peer group and the general market over the past five years. They find that DrPS´s are trading relatively high compared to historical numbers, which reduces the price potential in the opinion of the analysts.

4.3.5 Summary of the three reports

As described above, two of the three reports use an entity-perspective DCFCM, but no analyst uses a RIVM, which was found to be the most accurate FBVM in the LSA. However, analysts seem to focus on cash flows when using FBVMs rather than earnings, but all three analysts use earnings for the MBVM. The analysts using a DCFCM use detailed forecasts of accounting numbers to calculate FCFF. Nevertheless, RBC and Deutsche Bank use in some cases very different assumption such as the cost of equity which illustrates the dependence of those models on an analyst´s opinion. Moreover, although forecast horizons of at least eight years are used, TV still represents more than half of the value estimates and thus leaves the value estimate very sensitive to those assumption. The scenario analysis by RBC demonstrates that altering a few assumptions can lead to very different estimates. Even though a DCFCM is applied two out of three times, the analysts still use multiples to justify or supplement the value estimate. All analysts rely in some way on a MBVM using a forecasted earnings number as a value driver, which is in line with the findings of the LSA that the PE1 is more accurate than

FBVMs as well as the developed hypothesis. The stability of the firm´s financial performs is mentioned by analysts and supports both types of valuation.

The use of DCFCM in combination with a MBVM is in line with the developed hypothesis. This may be client driven as argued by Imam, Barker et al. (2008). However, the described findings are only specifically found for the analyzed firm DrPS and cannot be generalized. Analyst may use different models for different firms and industry.