**Journal of Economics and Behavioral Studies**
Vol. 6, No. 5, pp. 386-399, May 2014 (ISSN: 2220-6140)

# Precision, Consistency and Bias in Emerging Equity Markets

WS Nel*, BW Bruwer, NJ le Roux
University of Stellenbosch Matieland, South Africa
*snel@sun.ac.za

**Abstract:** The use of multiples is a popular approach employed by analysts to perform valuations. These multiples are based on optimal value drivers, the valuation performance of which should be underpinned by empirical findings from carefully designed, unbiased research initiatives. This paper firstly investigates the risk of biasing the design of market-based studies which aim to test the valuation performance of individual value drivers. The evidence revealed that, when testing the valuation performance of value drivers, there is an inherent risk of biasing the design of a study of this kind, and therefore, its outcome. Secondly, the paper presents evidence in support of the consistency of previous research findings regarding the valuation performance of individual value drivers in the South African market over the period 2001-2010. To this end, the paper introduces a new approach for the analysis of multi-dimensional equity valuation research data in the form of principal component analysis (PCA)-based biplots. Thirdly, the paper provides evidence that multiples-based modeling seems to be biased to the downside, which is an important consideration for analysts who choose to adjust their valuations outside of these models.

**Keywords:** *Emerging markets, JSE equity market, Multiples, South Africa, Valuation precision*

## 1. Introduction

Researchers focusing on the valuation precision of multiples-based value drivers often tend to select a limited number of value drivers to include in their analyses. However, limiting the selection of value drivers may constitute a biased approach, which, in turn, may lead to biased results. The bias risk is particularly acute when these cherry-picked value drivers are regarded as representatives of entire value driver categories, since it ignores the potential of individual value drivers to outperform their own and/or other value driver categories. When analyzing the valuation performance of value drivers it is of equal importance to assess the consistency of the valuation performance of individual value drivers over time. Unfortunately, many studies are designed over a relatively short time period, for example, five years or less, which may obscure a careful analysis of the consistency of the results over time. Therefore, it is imperative when designing a study of this kind to construct a sample of observations that covers a reasonable time frame. Given the design of the benchmark approach to multiples-based valuations, it is also important to assess any biased tendencies of multiples-based modeling. Although the evidence from the developed market literature suggests that multiples-based modeling is biased to the downside, no such evidence exists for emerging markets. Consequently, the focus of this paper is on the *modus operandi* when selecting value drivers to include in a study of this kind, specifically the potential risk of biasing the design of the study, which may produce misleading results. The paper also highlights the importance of assessing the consistency of the valuation performance of the individual value drivers over time. Lastly, this paper investigates the mispricing tendencies of multiples-based modeling, i.e. the tendency of the constructed multiples to over- or undervalues share prices on the JSE Securities Exchange (JSE). A complete list of acronyms/abbreviations is available in Appendix A. Section 2 provides evidence from prior research, while sections 3 and 4 present the data selection process and the research methodology. The research findings are presented in section 5 and concluding remarks are offered in section 6.

## 2. Literature Review

Multiples are constructed by scaling a specific market price variable by a corresponding value driver. The target company's equity value is then calculated as the product of such a multiple and the target company's actual value driver. The focus of this study is on the latter, specifically the ability of value drivers to approximate the market prices of shares. The evidence from the developed market literature suggests that earnings-based value drivers perform the most accurate equity valuations (Herrmann & Richter, 2003; Liu et al., 2002b; Cheng & McNamara, 2000). When conducting research on value drivers it is impractical to include all potential value drivers in a study. However, the selection of only a few individual value drivers carries an equal amount of risk. The inherent assumption when selecting a limited number of value drivers is that they are good representatives of entire value driver categories. However, if this assumption does not hold, it may constitute a biased approach. Herrmann and Richter (2003), for example, tested the valuation performance of only five value drivers, namely earnings (E), earnings before interest (EBI), earnings before interest depreciation and amortisation (EBIDA), book value of equity (BVE) and invested capital (IC). Similarly, Liu et al. (2002b) investigated the valuation performance of only four value drivers, namely earnings per share, dividend per share, cash flow per share and revenue per share, and neglected to include an asset-based value driver. In a similar vein, Cheng and McNamara (2000) compared the valuation performance of only two value drivers, namely earnings and book value of equity.

There are three points to note in this regard: Firstly, the value drivers selected in these three studies do not necessarily include the most accurate individual value drivers from the various value driver categories. Secondly, while a comparison of specific individual value drivers tested in these studies may have suggested a relative valuation performance ranking, this may not be an appropriate basis to generalize the findings on a value driver category basis. Thirdly, if the individual value drivers included in these three studies are not the most accurate value drivers from their respective value-driver categories, this may constitute a biased design, which, in turn, will result in a biased outcome. If there are individual value drivers, for example, that outperform their own and/or other value driver categories, this may refute the generalized findings from a value driver category-based analysis. This may partly explain why, on an intra-value driver category basis, the developed market literature offers conflicting results. Intra-value driver category performance-based research in developed markets tends to focus on earnings as a value driver category. Most researchers conclude that earnings before interest, tax, depreciation and amortization (EBITDA) and earnings before interest and tax (EBIT) are the most accurate earnings-based value drivers (Lie & Lie, 2002; Baker & Ruback, 1999). However, Schreiner and Spremann (2007) found evidence to the contrary. Their results indicated that, with the exception of sales and gross income, which are located higher up in the statement of comprehensive income, EBITDA performed the least accurate equity valuations. Schreiner and Spremann (2007) found that the top performers in terms of valuation precision were EBIT, earnings before tax (EBT) and E. Most researchers also conclude that forward multiples perform more accurate valuations than trailing multiples (Schreiner & Spremann, 2007; Lie & Lie, 2002; Kim & Ritter, 1999). Unfortunately, data limitations in South Africa obscure a detailed analysis in this regard.

Although some studies have increased their selection of value drivers, they tend to cover only a limited number of company years. Herrmann and Richter (2003), for example, tested the valuation performance of five value drivers over the three-year period 1997-1999 and Abukari, Jog and McConomy (2000), although including a wider selection of variables, only covered the five-year period 1992-1996. These short time periods make it difficult to assess the consistency of the results over time, which is an important consideration when assessing the valuation performance of value drivers. The superior performance of a value driver in a particular year does not guarantee its superiority over a number of years. Therefore, when analyzing pooled data that covers a prolonged period of time, say, ten years or more, the consistency of the results should be tested over shorter intervals, i.e. at least on an annual basis. Evidence from the developed market literature also suggests that, when employing the harmonic mean as averaging procedure, multiples-based modeling tends to be biased to the downside (Herrmann & Richter, 2003). Assessing whether multiples-based modeling tends to over- or underestimate share prices on the market is an important consideration since it may provide a theoretical basis for analysts to adjust their modeled outcomes. Therefore, it is important to assess whether the mispricing is sporadic or whether there are general biased tendencies to the up- or downside. These tendencies have not yet been investigated for emerging markets such as South Africa.

From an emerging market perspective, Nel et al. (2013c) established that, in the South African market, earnings-based multiples performed the most accurate valuations, followed by assets-, cash flow- and revenue-based multiples. In an extension of their original work, Nel et al. (2013c) extracted the most accurate individual value drivers from each of five value driver categories and compared their relative valuation performances, which produced the following precision ranking: HE, CgbO, OD, TA and R. Note that Nel et al. (2013c) included OD as part of the cash flow-based value driver category, whereas OD is isolated as a separate value driver category in this study. Although the study by Nel et al. (2013c) included a careful selection of value drivers, thereby mitigating the risk of a biased design, they neglected to elaborate on the consistency of their findings over the period 2001-2010. They also failed to investigate the biased tendencies associated with their applied methodology. With the various shortcomings highlighted above in mind, the aim of this paper is three-fold. Firstly, to highlight the inherent risk associated with the design of a study based on a selection of value drivers. Secondly, to investigate the consistency of individual value driver performance over time. Thirdly, to investigate bias tendencies associated with multiples-based modeling in emerging markets. To this end, this study elaborates on the valuation performance of the 16 individual value drivers contained in Table 1. As is evident from Table 1, these value drivers are selected from five different value driver categories, namely earnings, assets, dividends, cash flow and revenue for the period 2001-2010.[1] See Nel et al. (2013c) for a discussion on the shortcomings of each of these value driver categories. The paper also introduces a new approach for the analysis of multi-dimensional equity valuation research data in the form of principal component analysis (PCA)-based biplots, which are constructed to approximate graphical displays of the data.

**Data selection:** The following variables were extracted from the McGregor BFA database: Market capitalization (MCap), Shares in issue, Gross profit (GP), Earnings before interest, tax, depreciation and amortization (EBITDA), Earnings before interest and tax (EBIT), Profit after tax (PAT), Profit before tax (PBT), Headline earnings (HE), Total assets (TA), Invested capital (IC), Book value of equity (BVE), Turnover (R), Cash as operations, Increase/decrease in working capital, Net retained cash (NCIfOA), Cash generated (NCIfIA), Ordinary dividend (OD), Taxation paid, Fixed assets acquired, Net interest paid/received, Secondary tax on companies, Capital profits/losses on financial assets, Normal taxation included in extraordinary items, Total profit of an extraordinary nature and Sector. All key variables are defined in Appendix B. The data that were extracted from the McGregor BFA database were screened based on three criteria: 1) All multiples are positive, i.e. negative multiples were discarded since they are nonsensical and cannot be used; 2) The companies have at least three years of positive company year multiples, ensuring that selected companies have a reasonable history as a going concern; 3) Each sector has at least four observations that meet criteria 1) and 2) above. This ensures that the number of companies within each sector is not prohibitively small, preventing the situation where there are too few observations to warrant a realistic mean calculation. For the purposes of this study, companies were allocated to the sectors where they resided as at 31 December 2010.

The initial analysis of the data indicated the presence of a significant number of outliers (Nel et al., 2013a; b). Consequently, observations located outside of the 1st and 99th percentiles of the pooled observations were removed. Although the aim thereof was to eliminate extreme positive outliers, it was applied to the upper and the lower ends of the pooled observations, to prevent biasing the design of the study (Nel et al., 2013c). The final population of observations represents approximately 71% of the total number of listed companies on the JSE as at 31 December 2010 and approximately 91% of the market capitalisation of the companies listed on the JSE at the same date, which serves as a fair representation for the conclusions drawn. The 16 value drivers had varying sample sizes, ranging from 994 to 2 589 observations, with a total population of 31 467 observations for the period 2001-2010. From these observations, 16 multiples were constructed, i.e. multiples where the market price (P) was scaled by the 16 value drivers. Table 1 contains a summary of the 16 value drivers selected for this study and the five different value driver categories they reside in.

## 3. Methodology

Equity valuations based on equity multiples assume that a company's ($i$) actual equity value ($V_{it}^{e}$) at time ($t$) is equal to the product of an equity multiple ($\lambda_t^e$) and a specific value driver ($\alpha_{it}$) at that specific point in time, so that

$$V_{it}^{e} = \lambda_t^e \cdot \alpha_{it} \tag{1}$$

An out-of-sample peer group multiple ($\hat{\lambda}^{e}{}_{ct}$) is estimated for each company by calculating the harmonic mean of the multiples of all the other remaining companies in the same sector. The harmonic mean is used since most researchers regard it as a viable and unbiased estimator (Dittman & Maug, 2008; Bhojraj & Lee, 2002; Liu et al., 2002b; Beatty et al., 1999). The sector industry classification is applied, since previous research established that it was the optimal industry classification when conducting a cross-section analysis (Nel et al., 2013a). The application of an industry-specific approach to multiples is well established by research (Nel et al., 2013a; Nel, 2009a, b; Goedhart, Koller & Wessels, 2005; Liu, Nissim & Thomas, 2002a; Fernández, 2001; Barker, 1999).

**Table 1: Framework of multiples**

| | **Value drivers** | | | | |
|---|---|---|---|---|---|
| | **Earnings** | **Assets** | **Dividends** | **Cash flow** | **Revenue** |
| | GP | TA | OD | CgbO | R |
| | EBITDA | IC | | NCIfOA | |
| | EBIT | BE | | NCIfIA | |
| | PAT | | | FCFE | |
| | PBT | | | FCFF | |
| P | HE | | | | |

P - Market price
GP - Gross profit
EBITDA - Earnings before interest, tax, depreciation and amortization
EBIT - Earnings before interest and tax
PAT - Post-tax earnings
PBT - Pre-tax earnings
HE - Headline earnings
TA - Total assets
IC - Invested capital
BVE - Book value of equity
OD - Ordinary cash dividend
CgbO - Cash generated by operations
NCIfOA - Net cash inflow from operating activities
NCIfIA - Net cash inflow from investment activities
FCFE - Free cash flow to equity
FCFF - Free cash flow to the firm
R – Revenue

The peer group estimate of each company ( $\hat{\lambda}^{e}{}_{ct}$ ) is multiplied by the target company's actual value driver ( $\alpha_{it}$ ) to calculate an equity value prediction ( $\hat{V}_{it}^{e}$ ):

$$\hat{V}_{it}^{e} = \hat{\lambda}^{e}{}_{ct} \cdot \alpha_{it} \tag{2}$$

Subtracting Equation (1) from Equation (2) produces (3) for the calculation of the error margin (valuation error):

$$\hat{V}_{it}^{e} - V_{it}^{e} \tag{3}$$

Since companies with higher values tend to have higher valuation errors, it is anticipated that (3) will not be independent of value. Therefore, expressing (3) proportionally to $V_{it}^{e}$ will improve the efficacy of the estimate of the peer group multiple (Beatty et al., 1999). Consequently, the standardized form of (3), $\varepsilon_{it}$ , is expressed proportionally to $V_{it}^{e}$ , where

$$\varepsilon_{it} = \left| \frac{\hat{V}_{it}^{e} - V_{it}^{e}}{V_{it}^{e}} \right| \tag{4}$$

Functions for the calculation of $\varepsilon_{it}$ and the statistical analysis thereof were developed in the R-package, an open source programming language that lends itself to statistical analysis and graphics (R Development Core Team, 2012). Absolute and signed valuation errors are calculated for each company year and subsequently aggregated. The median valuation errors of the 16 value drivers are then compared to establish which value drivers offer the greatest degree of valuation precision.

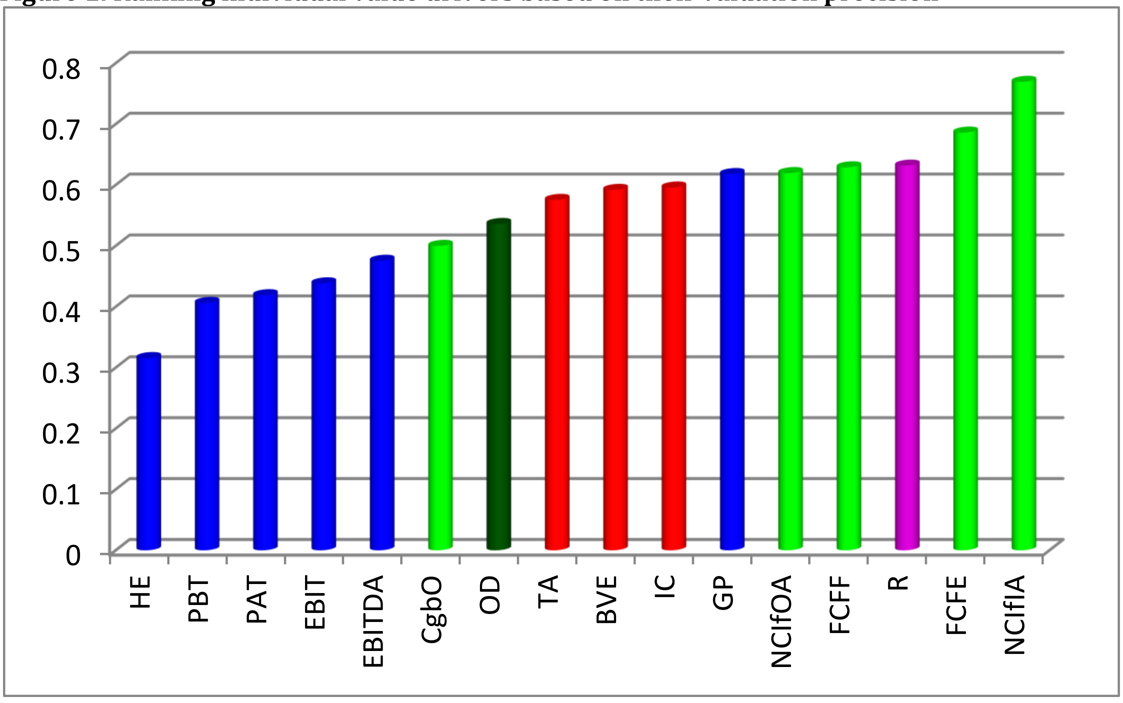
## 4. Results

Firstly, the valuation precision of the 16 individual value drivers is compared in order to ascertain whether there are incidences where individual value drivers outperform their respective and/or other, more accurate, value driver categories. If these exceptions do occur, they will confirm that there is an inherent risk when limiting the number of value drivers included in a study of this kind. This is followed by an analysis of the consistency of the results for the years 2001-2010. To this end, a two-dimensional biplot, which is based on PCA, is employed in order to assess the behaviour of the 16 value drivers over the period 2001-2010. From the biplot, an optimal one-dimensional scaling map is constructed, offering a linear display of the optimal ranking of the 16 value drivers over this period. The final analysis investigates whether the 16 multiples exhibit any mispricing tendencies, i.e. whether they are prone to under- or overvalue the market.

**Value driver bias and precision, based on pooled valuation errors:** The precision ranking (HE, CgbO, OD, TA and R) obtained by Nel et al. (2013c) should be viewed with the necessary amount of caution. An inter-value driver category comparison, based on the selection of single value drivers from each of the five value driver categories, may constitute a biased approach (Nel et al., 2013c). On closer examination of the observations underlying these results, one finds that, with the exception of GP, all the individual earnings-based value drivers offer a greater degree of valuation precision than CgbO. The best-in-category comparison performed by Nel et al. (2013c) merely serves to illustrate the magnitude of the superiority of HE *vis-á-vis* the other value drivers. A more appropriate analysis would be one that compares the valuation precision of all 16 individual value drivers over several years.

Consequently, Figure 1 depicts a comparison of the valuation precision of each of the 16 individual value drivers. From Figure 1, the danger of selecting single value drivers as representatives of entire value driver categories is evident. Comparing CgbO with GP, for example, may lead one to draw a faulty conclusion, i.e. that cash flow-based value drivers produce more accurate valuations compared to earnings-based value drivers. In this case, selecting a single value driver as representative of an entire value driver category will bias the outcome. Moreover, there are two individual value drivers that outperform their own and/or other value driver categories. From Figure 1, it is evident that CgbO achieves a higher level of valuation precision than OD, the entire asset category and GP. CgbO achieved a 6.72% higher degree of valuation precision than OD, 13.12%, 15.55% and 16.10% higher than TA, BVE and IC, respectively; and a 19.10% higher degree of valuation precision than GP. This is despite the fact that the cash flow value driver category's inter-value driver category performance, on average, placed it third among four value driver categories, notably behind earnings and assets (Nel et al., 2013c).

**Figure 1: Ranking individual value drivers based on their valuation precision**



Similarly, R, which produced the least accurate valuation results, outperforms two of the individual value drivers in the cash flow value driver category, namely FCFE and NCIfIA, by 7.92% and 17.89%, respectively. Also note that the entire asset-based value driver category, i.e. IC, BVE and TA, outperformed GP by 3.58%, 4.21% and 6.88%, respectively. However, an analysis of the entire pool of valuation errors for the period 2001-2010 does not necessarily reflect the consistency of the results over this period. An analysis of the annual valuation performance of the 16 value drivers is required to assess the consistency of the results.

**Consistency of value driver precision, based on annual valuation errors:** Table 2 contains a summary of the pooled and annual valuation errors of the 16 value drivers over the period 2001-2010. The multi-dimensional nature of the data contained in Table 2 complicates a careful assessment of the valuation performance of the 16 value drivers over the multi-year period. However, the biplot depicted in Figure 2 affords one the opportunity to depict the data contained in Table 2 in a two-dimensional format. For a more detailed discussion on the use of biplots see Gower et al. (2011).

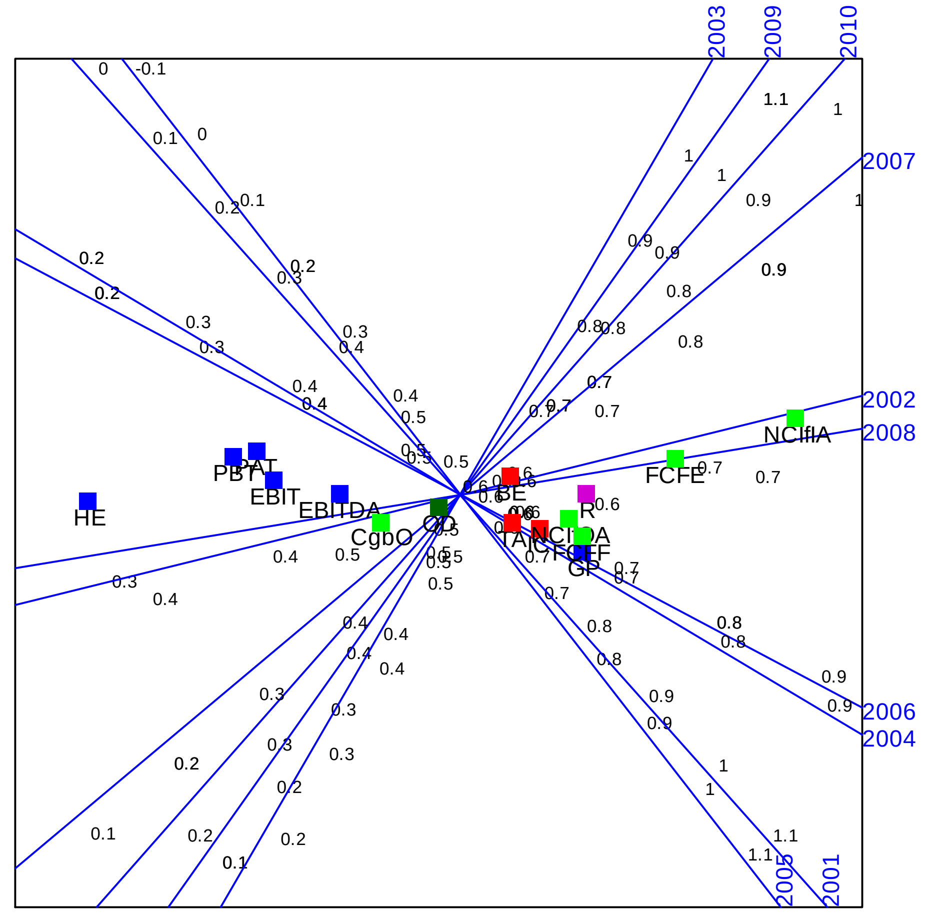
**Table 2: Actual median valuation errors: Pooled and annual**

| | | **Annual** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Pooled** | **2010** | **2009** | **2008** | **2007** | **2006** | **2005** | **2004** | **2003** | **2002** | **2001** |
| HE | 0.3156 | 0.3625 | 0.3656 | 0.3257 | 0.2946 | 0.2774 | 0.2679 | 0.2543 | 0.3044 | 0.3374 | 0.3704 |
| PBT | 0.4061 | 0.4414 | 0.4320 | 0.3661 | 0.3743 | 0.3388 | 0.3308 | 0.4420 | 0.5561 | 0.4367 | 0.4209 |
| PAT | 0.4188 | 0.4532 | 0.4353 | 0.3734 | 0.4112 | 0.3912 | 0.3692 | 0.4122 | 0.5585 | 0.4906 | 0.3897 |
| EBIT | 0.4383 | 0.4378 | 0.4404 | 0.3764 | 0.4430 | 0.4176 | 0.3960 | 0.4344 | 0.5045 | 0.4794 | 0.4403 |
| EBITDA | 0.4754 | 0.4878 | 0.4840 | 0.4241 | 0.4413 | 0.4818 | 0.4447 | 0.4846 | 0.5134 | 0.5208 | 0.5046 |
| CgbO | 0.4998 | 0.4613 | 0.5253 | 0.4341 | 0.4686 | 0.4686 | 0.5197 | 0.4830 | 0.5120 | 0.5347 | 0.6228 |
| OD | 0.5358 | 0.5672 | 0.4982 | 0.5462 | 0.5872 | 0.5032 | 0.5399 | 0.5389 | 0.4724 | 0.5774 | 0.5815 |
| TA | 0.5753 | 0.5493 | 0.5114 | 0.5280 | 0.5570 | 0.5956 | 0.5871 | 0.6234 | 0.6304 | 0.6275 | 0.6747 |
| BVE | 0.5918 | 0.6187 | 0.5687 | 0.5532 | 0.6022 | 0.6238 | 0.5891 | 0.5472 | 0.6342 | 0.5377 | 0.6036 |
| IC | 0.5957 | 0.5740 | 0.5124 | 0.5735 | 0.5519 | 0.6153 | 0.6487 | 0.6274 | 0.6518 | 0.6330 | 0.6708 |
| GP | 0.6178 | 0.5980 | 0.5558 | 0.5497 | 0.5710 | 0.7315 | 0.6917 | 0.7211 | 0.6228 | 0.5852 | 0.6670 |
| NCIfOA | 0.6194 | 0.5896 | 0.6276 | 0.5097 | 0.6295 | 0.6282 | 0.6723 | 0.6468 | 0.5797 | 0.6690 | 0.6828 |
| FCFF | 0.6288 | 0.5865 | 0.6449 | 0.6150 | 0.6086 | 0.6025 | 0.6693 | 0.6511 | 0.5702 | 0.5718 | 0.7780 |
| R | 0.6316 | 0.5751 | 0.6412 | 0.6388 | 0.6013 | 0.6762 | 0.6192 | 0.6103 | 0.6690 | 0.6278 | 0.7074 |
| FCFE | 0.6859 | 0.6660 | 0.7613 | 0.6582 | 0.7316 | 0.7012 | 0.6405 | 0.6393 | 0.6768 | 0.6736 | 0.7852 |
| NCIfIA | 0.7692 | 0.8019 | 0.8308 | 0.7153 | 0.8204 | 0.7554 | 0.7286 | 0.7806 | 0.7949 | 0.7520 | 0.7671 |

**Table 3: Predictivity readings over the period 2001-2010**

| **Years** | **2010** | **2009** | **2008** | **2007** | **2006** | **2005** | **2004** | **2003** | **2002** | **2001** |
|---|---|---|---|---|---|---|---|---|---|---|
| Predictivity | 0.957 | 0.914 | 0.924 | 0.963 | 0.952 | 0.988 | 0.938 | 0.821 | 0.901 | 0.938 |

**Figure 2: PCA biplot reflecting the consistency of the relative valuation performance of the 16 value drivers over the period 2001-2010**




Note: The R code for constructing the PCA biplots utilises the UBbipl package, which is available at the following link: http://dl.dropbox.com/u/17860902/UBbipl_1.0.zip

**Table 4: Correlation matrix of the median annual valuation errors over the period 2001-2010**

| | **Annual** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **2010** | **2009** | **2008** | **2007** | **2006** | **2005** | **2004** | **2003** | **2002** | **2001** |
| 2010 | 1.0000 | | | | | | | | | |
| 2009 | 0.9168 | 1.0000 | | | | | | | | |
| 2008 | 0.9320 | 0.8985 | 1.0000 | | | | | | | |
| 2007 | 0.9746 | 0.9433 | 0.9439 | 1.0000 | | | | | | |
| 2006 | 0.9082 | 0.8499 | 0.9206 | 0.9106 | 1.0000 | | | | | |
| 2005 | 0.8787 | 0.8202 | 0.9060 | 0.8982 | 0.9610 | 1.0000 | | | | |
| 2004 | 0.9021 | 0.8232 | 0.8851 | 0.8947 | 0.9484 | 0.9582 | 1.0000 | | | |
| 2003 | 0.8491 | 0.7898 | 0.7962 | 0.8130 | 0.8357 | 0.7632 | 0.8491 | 1.0000 | | |
| 2002 | 0.8976 | 0.8584 | 0.8786 | 0.9304 | 0.8997 | 0.9060 | 0.9206 | 0.8457 | 1.0000 | |
| 2001 | 0.8365 | 0.8701 | 0.9271 | 0.8886 | 0.9071 | 0.9473 | 0.8967 | 0.7198 | 0.8759 | 1.0000 |

**PCA biplot exhibiting the consistency of value driver precision:** The PCA quality reading of the biplot in Figure 2 is 93.55%, suggesting that the approximations in Figure 2 were achieved with a negligible loss of data accuracy. These readings were obtained from the output in R, the code that was applied in this study. This is confirmed by the annual predictivity readings, as contained in Table 3. The greatest loss in accuracy occurs in 2003, reflected in the predictivity reading of 82.1%, which is still very accurate. For a more detailed discussion on the use of biplots see Gower et al. (2011). Each of the ten years over the period 2001-2010 is represented by a separate calibrated axis in Figure 2. Note that the axes are colour-coded, i.e. each year reflects the colour of the value driver category that performed the most accurate valuations in that particular year. The point of intersection (origin) of the ten axes represents the means of the 16 value drivers for each of the ten years. The valuation errors of the 16 value drivers are depicted relative to each other and relative to the mean for each of the ten years. The more accurate value drivers, i.e. the value drivers with the smaller valuation errors, are located to the left of the origin, while the less accurate value drivers are located to the right of the origin.

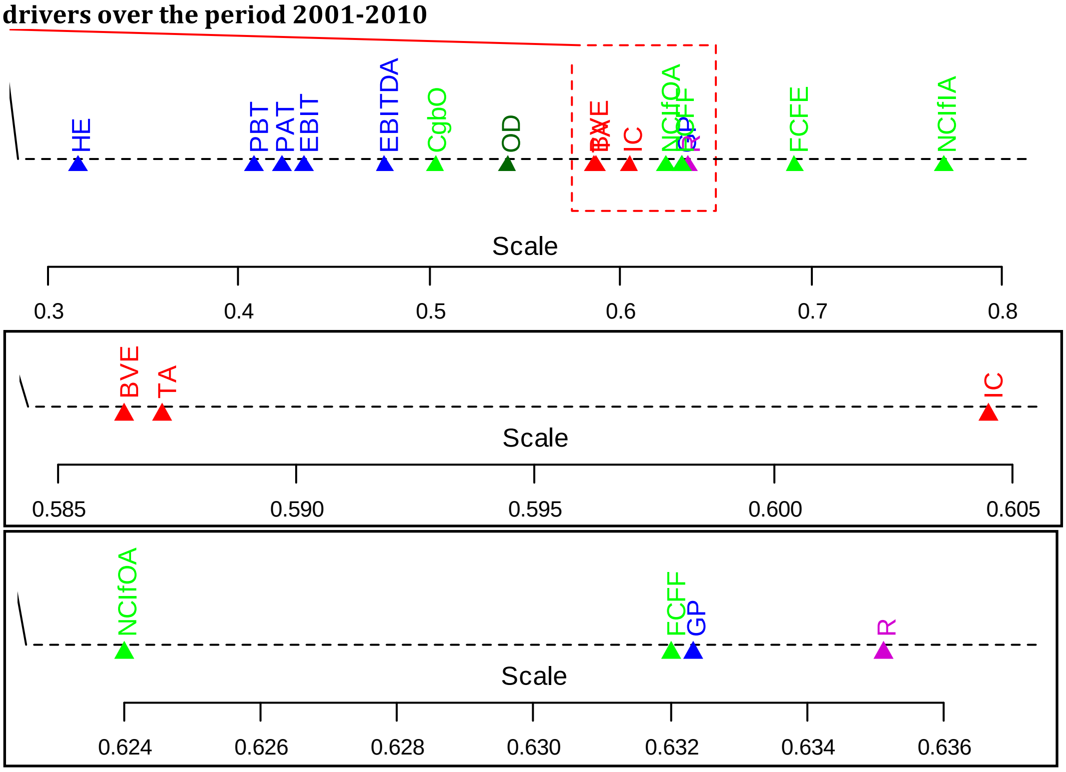
Upon consideration of the location of the five value driver categories relative to the origin, it is evident that, with the exception of GP, earnings-based value drivers cluster towards the left of the origin. This indicates that they produce valuation errors below the mean of the 16 value drivers for each of the ten years. Therefore, earnings-based value drivers generally produce the greatest degree of valuation precision over the multi-year period. Dividend- and asset-based value drivers cluster around the origin, indicating that they produce results close to the mean valuation error for each of the ten years, i.e. they produce valuations with average levels of precision. However, whereas OD consistently produces valuation errors below the mean, the asset-based cluster consistently offers valuation errors above the mean. Cash flow-based value drivers, with the exception of CgbO, cluster towards the right of the origin, indicating that they, along with revenue, produce results that are higher than the mean valuation error for each of the ten years, i.e. they produce valuations with the least degree of precision. The location of these five value driver clusters relative to each other, allows one to derive their relative valuation performance in terms of valuation precision. Earnings-based value drivers generally perform the most accurate equity valuations. Dividend- and asset-based value drivers produce average valuation results and cash flow- and revenue-based multiples produce the least accurate valuation results. The location of the value driver clusters relative to the mean, and each other, concurs with the original findings by Nel et al. (2013c).

When considering the performance of individual value drivers within each of the five value driver categories, exceptions to the clusters can be identified. Apart from being the only value driver that produces the most accurate equity valuations among earnings-based value drivers, HE is also the most accurate value driver among all 16 value drivers. HE consistently exhibits superior explanatory power in terms of valuation precision for each of the ten years between 2001 and 2010. In Figure 3, this is reflected by the fact that all the axes are blue. In Figure 2, the distance between its location and the location of the other earnings-based value drivers, and the origin, reflects the magnitude of its superiority. GP is the only earnings-based value driver that is located to the right of the origin, which reflects its consistent sub-optimal valuation performance over the period 2001-2010 compared to the mean of all 16 value drivers, and compared to the earnings cluster. GP’s distance from the other earnings-based value drivers, and the origin, reflects the magnitude of its inferior valuation performance.

The best performer in the cash flow cluster is CgbO, which is also the only cash flow-based value driver that is located to the left of the origin, indicating its ability to produce valuation errors below the mean. CgbO consistently exhibits superior explanatory power compared to the cash flow cluster in terms of valuation precision for each of the ten years between 2001 and 2010. In Figure 2, the distance between the location of CgbO and the location of the other cash flow-based value drivers reflects the magnitude of its superiority relative to the cash flow value driver category. Situated to the far right of the origin, FCFE and NCIfIA are the poorest performers of the cash flow cluster and of all 16 value drivers. FCFE and NCIfIA consistently offer significantly less explanatory power compared to the other 14 value drivers. The distance between their location and that of the other 14 value drivers, from the origin, reflects the magnitude of their sub-optimal performance. There are no extraordinarily strong or weak performers in the asset-based cluster. All three asset-based value drivers are fairly closely located, indicating that they all offer average results in terms of valuation precision. The dividend-based value driver, OD, tends towards the mean, generally producing valuation errors only marginally lower than the mean. OD consistently produces these results over the period 2001-2010. Revenue, on the other hand, is located to the right of the origin, reflecting its consistent sub-optimal valuation performance.

**Optimal one-dimensional scaling exhibiting the consistency of value driver precision:** The medians of the pooled valuation errors contained in Table 2 (that were used to assess the valuation performance of the 16 individual value drivers) do not reflect the consistency of the valuation performance of these value drivers over time. However, the biplot displayed in Figure 2 affords one the opportunity to assess the valuation performance of the 16 individual value drivers over the period 2001-2010. It offers a more comprehensive and objective view of the relative valuation performance of the 16 value drivers over time. The correlation matrix of the median annual valuation errors, as contained in Table 4, shows that all the years are highly and positively correlated, i.e. all pair wise correlations are between 0.7198 and 0.9746. Therefore, all elements of the first principal component resulting from a PCA of the median annual valuation errors will have the same sign and can be regarded as size vectors. From Figure 2, the x-coordinates of the points in the PCA biplot can be used to affect a linear transformation to a convenient one-dimensional optimal performance scale for the 16 value drivers. The set of optimal scores is depicted in Figure 3. See Greenacre (2007) for a detailed description of optimal one-dimensional scaling. For ease of interpretation, the scores are set between a minimum of 0.3156 and a maximum of 0.7692.

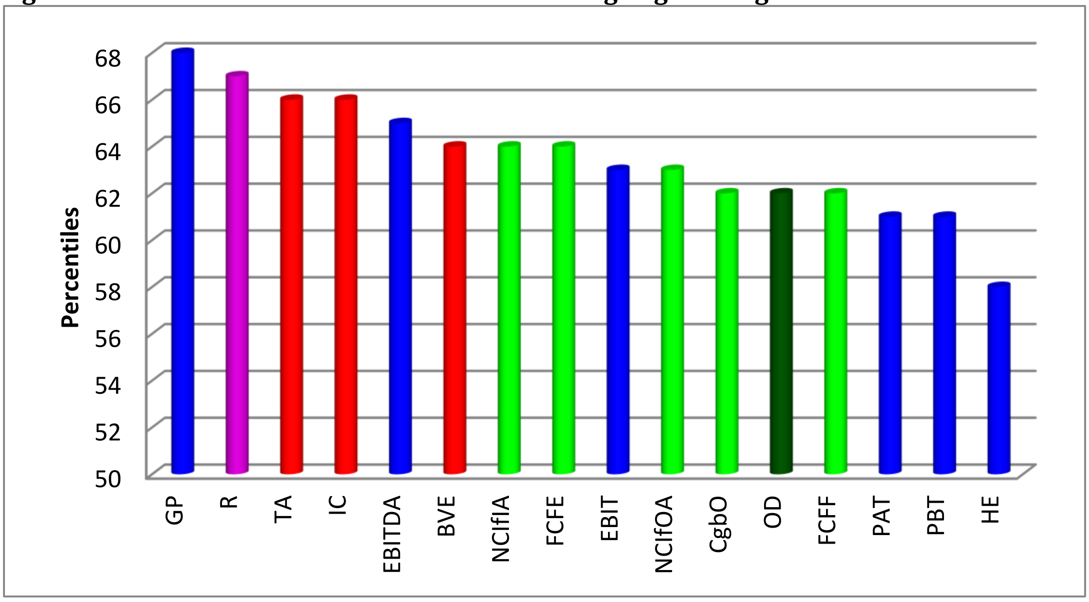
**Figure 3: Optimal one-dimensional scaling of the relative valuation performance of all 16 value drivers over the period 2001-2010**




Note the dashed red block in the proximity of the scaling value of 0.60. The red block encapsulates a cluster of seven value drivers, whose relative positions are obscured by the fact that their scaling values are in close proximity to each other. Subsequently, two magnified illustrations of the red block are provided in the rectangles below the original scaling in Figure 3. Figure 3 offers a one-dimensional linear display of the optimal scaling values for all 16 individual value drivers, confirming the superior valuation performance of HE. The location of HE to the far left of the linear display, with a scaled value of 0.3156, reflects its superior explanatory power *vis-á-vis* the other value drivers over the period 2001-2010. As with Figure 2, the magnitude of HE's superior valuation performance is illustrated by the distance between HE and the other 15 value drivers. The scaling values displayed in Figure 3 confirm the superior explanatory power offered by earnings-based value drivers and the inferior explanatory power offered by the cash flow- and revenue-based value drivers. Dividend- and asset-based value drivers offered average results in terms of valuation precision. Equally evident from Figure 3, in terms of scaling values and distance from the other value drivers, is the underperformance of FCFE and NCIfIA, with scaling values of 0.6913 and 0.7692, respectively.

**Mispricing tendencies of multiples-based modeling:** The analysis of the valuation performance of the 16 value drivers thus far was based on absolute valuation errors. However, these valuation errors do not reflect the tendencies of the value drivers to under- or overestimate the actual share prices on the JSE. In order to assess any biased tendencies in the data, one has to analyze the signed valuation errors. Given the design of this study, specifically the specification in Equation (4), negative $\varepsilon_{it}$ will infer that the multiples-based modeling undervalues share prices on the JSE and *vice versa*, i.e. positive $\varepsilon_{it}$ will infer that multiples-based modeling overvalues share prices on the JSE. Figure 4 depicts the percentiles of each of the 16 value drivers' valuation errors that exhibit negative signs. As is evident from Figure 4, the baseline indicates that all the median signed valuation errors are negative, which suggests that all 16 value drivers are biased to the downside, i.e. they tend to undervalue JSE share prices. The means of all 16 value drivers are positive, which, in part, stems from the design of this study. Although the valuation errors cannot be much smaller than zero, they can be substantially larger than zero. Therefore, the potential magnitude of positive outliers far exceeds the potential magnitude of negative outliers. The latter is confirmed by the average range among the 16 individual value drivers, which lies between -0.9890 and 55.0937, indicating that the size of the positive outliers is far greater than the size of the negative outliers. Means are also far more susceptible to outliers than medians, which largely explain why researchers regard the median as a more robust measure of central tendency than the mean (Bhojraj & Lee, 2002; Liu et al., 2002b; Beatty et al., 1999).

**Figure 4: Percentiles of valuation errors exhibiting negative signs**




As is evident from Figure 4, the magnitude of the tendency to undervalue shares varies for each individual value driver. The percentiles exhibiting negative valuation errors vary between 58% and 68%, indicating that the predominant tendency is to undervalue JSE share prices. This tendency was particularly acute with GP, R, TA and IC, where approximately two thirds of the observations had negative signs.

## 5. Conclusion

This paper highlights the danger of cherry-picking individual value drivers as representatives of entire value driver categories. Therefore, a more appropriate comparison was performed, where the valuation performance of all 16 individual value drivers was considered. The evidence suggests that individual value drivers may outperform their own and/or other value driver categories. CgbO produced more accurate valuations than OD, the entire assets category and GP, with an increased level of precision ranging between 6.72% and 19.10%. Similarly, revenue outperforms FCFE and NCIfIA by 7.92% and 17.89%, respectively, while the entire asset-based value driver category outperformed GP by an increased level of precision, ranging from 3.58% to 6.88%. Secondly, the consistency of the valuation performance of the 16 value drivers was tested over the period 2001-2010. However, the multi-dimensional nature of the data presented a challenge in this regard, since it obscured a comprehensive grasp of the relative valuation performance of all 16 value drivers for each observation year. The use of biplots, which can accommodate the analysis and visualisation of a multitude of variables of this nature in the form of calibrated axes, proved very effective in this regard. To this end, a PCA-based, two-dimensional biplot was employed to assess the behaviour of the 16 value drivers over this period.

From the biplot, an optimal one-dimensional scaling was constructed, offering a linear display of the optimal ranking of the 16 value drivers over this period. The results indicated that HE consistently exhibited superior explanatory power in terms of valuation precision for each of the ten years between 2001 and 2010. All three asset-based value drivers were relatively closely located, indicating that they all offer similar results in terms of valuation performance. OD tended towards the mean, generally producing valuation errors only marginally lower than the mean over the period 2001-2010. Revenue was located to the right of the origin, reflecting its consistent sub-optimal valuation performance. CgbO was the only cash flow-based value driver that produced valuation errors below the mean, consistently exhibiting superior explanatory power compared to the rest of the cash flow cluster for each of the ten years between 2001 and 2010. The worst valuation performances by far were produced by FCFE and NCIfIA, which consistently offered significantly less explanatory power compared to the other 14 value drivers. These research findings have both theoretical and practical implications. Firstly, from a theoretical perspective, the research results emphasize the potential pitfalls when designing a study of this kind. Of particular concern in this respect is the tendency of academic researchers to cherry-pick individual value drivers and regard them as appropriate representatives of entire value driver categories. Equally important is assessing the consistency of the results over time. Failure to take cognizance of these findings may produce misleading results.

Secondly, from a practical perspective, analysts should take cognizance of the relative valuation precision of the various individual value drivers and the consistency of these results over time. The research results indicate that the magnitude of the loss in valuation precision accompanying the construction of sub-optimal multiples may be substantial. The results are of particular interest to analysts, who typically have a preference for earnings-based value drivers. The implication is that analysts should be scaling market prices with HE when constructing multiples, particularly earnings-based multiples. The superior valuation precision of HE-based multiples, in particular, was consistent over the period 2001-2010. Lastly, the evidence also suggests that multiples-based modeling tends to be biased to the downside. All 16 value drivers indicated a tendency to undervalue the share prices on the JSE. The percentile of each value driver exhibiting negative valuation errors varied between 58% and 68%, indicating that in some cases, notably GP, R, TA and IC, up to two thirds of the observations exhibited a predominant tendency to undervalue share prices on the JSE. The downside bias of multiples-based modeling is an important consideration for analysts, who typically choose to apply ex-model adjustments when employing multiples-based models.

**References**


Abukari, K., Jog, V. & McConomy, B. J. (2000). The role and the relative importance of financial statements in equity valuation, Working Paper, Wilfred Laurier University, Ontario.

Baker, M. & Ruback, R. S. (1999). Estimating industry multiples, Working Paper, Harvard University, Cambridge.

Barker, R. G. (1999). Survey and market-based evidence of sector-dependence in analysts' preferences between the dividend yield and price-earnings ratio valuation models. *Journal of Business Finance and Accounting,* 26(3&4), 393-418.

Beatty, R. P., Riffe, S. M. & Thompson, R. (1999). The method of comparables and tax court valuations of private companies – An empirical investigation. *Accounting Horizons,* 13(3), 177-199.

Bhojraj, S. & Lee, M. C. (2002). Who is my peer? A valuation-based approach to the selection of comparable companies. *Journal of Accounting Research,* 40(2), 407-439.

Cheng, C. S. A. & McNamara, R. (2000). The valuation accuracy of the price-earnings and price-book benchmark valuation methods. *Review of Quantitative Finance and Accounting,* 15(4), 349-370.

Dittmann, I. & Maug, E. (2008). Biases and error measures: How to compare valuation methods, Working Paper, Erasmus University, Rotterdam.

Fernández, P. (2001). Valuation using multiples. How do analysts reach their conclusions? Working Paper, IESE Business School, Madrid.

Goedhart, M., Koller, T. & Wessels, D. (2005). The right role for multiples in valuation. *McKinsey on Finance*, 15, 7-11.

Gower, J., Lubbe, S. & Le Roux, N. (2011). Understanding Biplots, Chichester: John Wiley & Sons, Ltd.

Greenacre, M. (2007). *Correspondence Analysis in Practice* (2nd Ed), London: Chapman and Hall/CRC.

Herrmann, V. & Richter, F. (2003). Pricing with performance-controlled multiples. *Schmalenbach Business Review,* 55(3), 194-219.

Kim, M. & Ritter, R. (1999). Valuing IPOs. *Journal of Financial Economics*, 53(3), 409-437.

Lie, E. & Lie, H. (2002). Multiples used to estimate corporate value. *Financial Analysts Journal*, 58(2), 44-54.

Liu, J., Nissim, D. & Thomas, J. (2002a). Equity valuation using multiples. *Journal of Accounting Research*, 40(1), 135-172.
Liu, J., Nissim, D. & Thomas, J. (2002b). International equity valuation using multiples, Working Paper, University of California at Los Angeles (Anderson Graduate School of Management).
Nel, W. S., Bruwer, B. W. & Le Roux, N. J. (2013a). The impact of industry classification on the valuation accuracy of multiples in the South African capital market. *International Business and Economics Research Journal*, 12(1), 79-102.
Nel, W. S., Bruwer, B. W. & Le Roux, N. J. (2013b). Equity- and entity-based multiples in emerging markets: Evidence from the JSE Securities Exchange. *Journal of Applied Business Research,* 13(3), 829-852.
Nel, W. S., Bruwer, B. W. & Le Roux, N. J. (2013c). The valuation performance of equity-based multiples in South Africa. Paper presented at the 52nd European International Academic Conference. 9 to 11 June 2013. Paris, France.
Nel, W. S. (2009a). The use of multiples in the South African equity market: Is the popularity of the price earnings ratio justifiable from a sector perspective? *Meditari Accountancy Research,* 17(2), 101-115.
Nel, W. S. (2009b). Methods of choice in the valuation of ordinary shareholders' equity. *Meditari Accountancy Research,* 17(2), 117-135.
R Development Core Team. (2012). R: A language and environment for Statistical computing, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.Rproject.org/.
Schreiner, A. & Spremann, K. (2007). Multiples and their valuation accuracy in European equity markets, Working Paper, University of Saint Gallen, Frankfurt.

**Appendix A: Acronyms**

| **Acronym/Abbreviation** | **Description** |
|---|---|
| BFA | Bureau of Financial Analysis |
| BVE | Book value of equity |
| CgbO | Cash generated by operations |
| DPS | Dividend per share |
| E | Earnings |
| ε | Error term |
| EBI | Earnings before interest |
| EBIDA | Earnings before interest, depreciation and amortisation |
| EBIT | Earnings before interest and tax |
| EBITDA | Earnings before interest, tax, depreciation and amortisation |
| EBT | Earnings before tax |
| EPS | Earnings per share |
| EY | Earnings yield |
| FCFE | Free cash flow to equity |
| FCFF | Free cash flow to the firm |
| GP | Gross profit |
| HE | Headline earnings |
| *i* | Company *i* |
| IC | Invested capital |
| IMP | Potential percentage improvement |
| JSE | JSE Securities Exchange |
| MCap | Market capitalisation |
| N | Number of observations |
| NCIfIA | Net cash inflow from investing activities |
| NCIfOA | Net cash inflow from operating activities |
| OD | Ordinary cash dividend |
| P | Market price |
| PAT | Profit after tax |
| PBT | Profit before tax |
| PCA | Principal component analysis |
| PwC | PricewaterhouseCoopers |
| R | Revenue |
| SEC | Securities and Exchange Commission |

| | |
|---|---|
| $t$ | Time period $t$ |
| TA | Total assets |
| UK | United Kingdom |
| USA | United States of America |
| $\lambda_t^e$ | Equity multiple |
| $\hat{\lambda}^e{}_{ct}$ | Estimated peer group equity multiple at time period $t$ |
| $\alpha_{it}$ | Actual value driver |
| $V_{it}^e$ | Actual value of equity of company $i$ at time period $t$ |
| $\hat{V}_{it}^e$ | Estimated value of equity of company $i$ at time period $t$ |

**Appendix B: Classification of variables**
All data were extracted from the McGregor BFA database. The classifications were largely derived from the descriptions as presented in the McGregor BFA user manuals.

**Market price variable**
1. Market capitalization (MCap) represents the market value of an entity's issued ordinary share capital. MCap is calculated by multiplying the market price per share as at the entity's financial year end with the issued volume of shares at the same date.

**Earnings-based multiples**
2. Gross profit (GP) represents and is calculated as the difference between revenue or revenue and the cost of revenue.
3. Earnings before interest, taxation, depreciation and amortization (EBITDA) represent an entity's earnings before interest, taxation, depreciation and amortization. It is calculated by taking EBIT and adding back depreciation and amortization.
4. Earnings before interest and tax (EBIT) represent an entity's earnings before interest and taxation. It is calculated by taking income before taxation and adding back interest.
5. Profit before tax (PBT) represents an entity's net profit, including realised profits and all losses of an extraordinary nature, after interest, but before taxation. It is calculated by taking profit before interest and taxation and deducting interest.
6. Profit after tax (PAT) represents an entity's net profit, including realised profits and all losses of an extraordinary nature, after interest and taxation. It is calculated by taking PBT and deducting taxation.
7. Headline earnings (HE) represents an entity's earnings generated by normal operational activities. It is calculated by taking PAT and adding back profits/losses associated with non-core operational activities, such as the sale of fixed assets or the termination of discontinued operations.

**Book value-based multiples**
1. Total assets (TA) represent the total of all the tangible assets employed by the entity. It is calculated by adding total fixed assets, total long-term investments and total current assets.
2. Invested capital (IC) represents the total cash investment by fund providers. It is calculated by deducting cash and cash equivalents from TA.
3. Book value of equity (BVE) represents the equity of the ordinary shareholders. It is calculated by adding ordinary share capital and reserves; and deducting the cost of control of subsidiaries and intangible assets.

**Revenue-based multiple**
1. Turnover (R) represents the gross revenue or revenue of the entity.

**Cash flow-based multiples**
2. Cash generated by operations (CgbO) represents pre-tax cash flows net of working capital requirements. It is calculated by taking operating profits, adding back non-cash items and deducting changes in working capital.
3. Net cash inflow from operating activities (NCIfOA) represents post-tax operational cash flows. It is calculated by taking CgbO and deducting net interest, net dividends and taxation.

4. Net cash inflow from investment activities (NCIfIA) represents post-tax operational cash flows net of fixed capital requirements. It is calculated by taking NCIfOA and deducting acquisitions of fixed capital items net of capital gains tax.
5. Ordinary dividend (OD) represents the amount of dividends paid to ordinary shareholders as per the cash flow statement.
6. Free cash flow to the firm (FCFF) represents post-tax cash flows that are available to be distributed to all the fund providers of an entity, net of capital requirements to grow or maintain the business. It is calculated by taking NCIfIA and adding back non-operational items, such as net interest and net dividends.
7. Free cash flow to equity (FCFE) represents post-tax cash flows that are available to be distributed to all the equity fund providers of an entity, net of capital requirements to grow or maintain the business. It is calculated by taking FCFF and adding/deducting debt capital movements and interest paid.