# THE DEVELOPMENT OF OPTIMAL COMPOSITE MULTIPLES MODELS FOR THE PERFORMANCE OF EQUITY VALUATIONS OF LISTED SOUTH AFRICAN COMPANIES: AN EMPIRICAL INVESTIGATION

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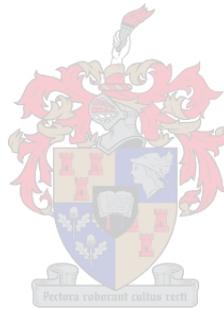
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DECLARATION

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ABSTRACT

The practice of combining single-factor multiples (SFMs) into composite multiples models is underpinned by the theory that various SFMs carry incremental information, which, if encapsulated in a superior value estimate, largely eliminates biases and errors in individual estimates. Consequently, the chief objective of this study was to establish whether combining single value estimates into an aggregate estimate will provide a superior value estimate *vis-á-vis* single value estimates.

It is envisaged that this dissertation will provide a South African perspective, as an emerging market, to composite multiples modelling and the multiples-based equity valuation theory on which it is based. To this end, the study included 16 SFMs, based on value drivers representing all of the major value driver categories, namely earnings, assets, dividends, revenue and cash flows.

The validation of the research hypothesis hinged on the results obtained from the initial cross-sectional empirical investigation into the factors that complicate the traditional multiples valuation approach. The main findings from the initial analysis, which subsequently directed the construction of the composite multiples models, were the following:

Firstly, the evidence suggested that, when constructing multiples, multiples whose peer groups are based on a combination of valuation fundamentals perform more accurate valuations than multiples whose peer groups are based on industry classifications. Secondly, the research results confirmed that equity-based multiples produce more accurate valuations than entity-based multiples. Thirdly, the research findings suggested that multiples models that are constructed on earnings-based value drivers, especially HE, offer higher degrees of valuation accuracy compared to multiples models that are constructed on dividend-, asset-, revenue- or cash flow-based value drivers.

The results from the initial cross-sectional analysis were also subjected to an industry analysis, which both confirmed and contradicted the initial cross-sectional-based evidence. The industry-based research findings suggested that both the choice of

optimal Peer Group Variable (PGV) and the choice of optimal value driver are industry-specific.

As with the initial cross-sectional analysis, earnings-based value drivers dominated the top positions in all 28 sectors that were investigated, while HE was again confirmed as the most accurate individual driver.

However, the superior valuation performance of multiples whose peer groups are based on a combination of valuation fundamentals, as deduced from the cross-sectional analysis conducted earlier, did not hold when subjected to an industry analysis, suggesting that peer group selection methods are industry-specific.

From this evidence, it was possible to construct optimal industry-specific SFMs models, which could then be compared to industry-specific composite models. The evidence suggested that composite-based modelling offered, on annual average, between 20.21% and 44.59% more accurate valuations than optimal SFMs modelling over the period 2001 to 2010.

The research results suggest that equity-based composite modelling may offer substantial gains in precision over SFMs modelling. These gains are, however, industry-specific and a *carte blanche* application thereof is ill advised. Therefore, since investment practitioners' reports typically include various multiples, it seems prudent to consider the inclusion of composite models as a more accurate alternative.

OPSOMMING

Die praktyk om Enkelfaktor Veelvoude (EFVe) te kombineer in saamgestelde veelvoudmodelle word ondersteun deur die teorie dat verskillende EFVe oor inkrementele inligting beskik, wat, indien dit in 'n superieure waardeskatting opgeneem word, grootliks vooroordele en foute in individuele skattings elimineer. Gevolglik was die hoofdoel van hierdie studie om vas te stel of die kombinering van verskeie enkelfaktor waardeskattings in 'n totale waardeskatting 'n superieure waardeskatting sal verskaf *vis-á-vis* enkelfaktor waardeskattings.

Dit word voorsien dat hierdie proefskrif 'n Suid-Afrikaanse perspektief, as 'n ontluikende mark, sal bied aangaande saamgestelde veelvoudmodellering en die veelvoud-gebaseerde ekwiteitswaardasie-teorie waarop dit gebaseer is. Hiermee ten doel, sluit hierdie studie 16 EFVe in, gebaseer op waardedrywers wat al die vernaamste waardedrywerkategorieë, naamlik verdienste, bates, dividende, omset en kontantvloeie, verteenwoordig.

Die bevestiging van die navorsingshipotese is afhanklik van die resultate soos bekom vanuit die aanvanklike dwarsdeursnee-empiriese ondersoek na die faktore wat die tradisionele veelvoudwaardasieproses kompliseer. Die hoofbevindinge van die aanvanklike ontleding, wat daarna rigtinggewend was vir die komposisie van die saamgestelde veelvoudmodelle, was die volgende:

Eerstens, dui die bewyse daarop dat, wanneer veelvoude saamgestel word, veelvoude waarvan die portuurgroepe op 'n kombinasie van fundamentele waardasie-veranderlikes gebaseer is, meer akkurate waardasies lewer as veelvoude waarvan die portuurgroepe op industrie-klassifikasies gebaseer is. Tweedens, het die navorsingsresultate bevestig dat ekwiteitsgebaseerde veelvoude meer akkurate waardasies lewer as entiteitsgebaseerde veelvoude. Derdens, toon die navorsingsbevindinge dat veelvoudmodelle wat saamgestel word uit verdienste-gebaseerde waardedrywers, veral wesensverdienste (WV), hoër grade van waardasie-akkuraatheid bied in vergelyking met veelvoudmodelle wat saamgestel word uit dividend-, bate-, omset- of kontantvloei-gebaseerde waardedrywers.

v

Die resultate van die aanvanklike dwarsdeursnee-ontleding is ook onderwerp aan 'n industrie-ontleding, wat die aanvanklike bevindinge van die dwarsdeursnee-ontleding beide bevestig en weerspreek het. Die bevindinge vanaf die industrie-ontleding dui daarop dat beide die keuse van optimale Portuurgroepveranderlike (PGV) en die optimale keuse van waardedrywer, industrie-spesifiek is.

Soos met die aanvanklike dwarsdeursnee-ontleding, het verdienste-gebaseerde waardedrywers die top posisies by al 28 sektore wat ondersoek is, gedomineer, terwyl WV weer as die akkuraatste individuele waardedrywer bevestig is.

Die superieure waardasie-resultate van veelvoude waarvan die portuurgroepe gebaseer was op 'n kombinasie van fundamentele waardasie-veranderlikes, soos afgelei uit die aanvanklike dwarsdeursnee-ontleding, het egter nie dieselfde resultate gelewer op 'n per sektor basis nie, wat aandui dat portuurgroep seleksiemetodes industrie-spesifiek is.

Vanuit hierdie bevindinge was dit moontlik om optimale EFV-modelle saam te stel, wat dan vergelyk kon word met industrie-spesifieke saamgestelde veelvoudmodelle. Die bevindinge het voorgestel dat saamgestelde modellering gemiddeld jaarliks, tussen 20.21% en 44.59% meer akkurate waardasies gelewer het as optimale EFV-modellering oor die tydperk 2001 tot 2010.

Die navorsingsresultate dui aan dat ekwiteitsgebaseerde saamgestelde modellering aansienlike toenames in waardasie-akkuraatheid mag bewerkstellig bo dié van EFV-modellering. Hierdie toenames is egter industrie-spesifiek en 'n *carte blanche* toepassing daarvan is nie aan te beveel nie. Gevolglik, aangesien beleggingspraktisyns se verslae tipies verskeie veelvoude insluit, blyk dit redelik om die insluiting van saamgestelde modelle as 'n meer akkurate alternatief te oorweeg.

ERKENNINGS

'n Mens kan nie anders as om in geestelike verwondering te staan dat die Hemelse Vader vir my die geleentheid gegun het om hierdie Ph.D te voltooi nie, veral nie met twee klein, en uiters energieke, kinders nie.

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LIST OF ACRONYMS/ABBREVIATIONS

Used in general body of text

Acronym/Abbreviation	Description
Act	Actual
BFA	Bureau of Financial Analysis
BRICS	Brazil, Russia, India, China and South Africa
BVE	Book Value of Equity
CAGRs	Compound Annual Growth Rates
CF	Earnings plus non-cash charges
CFO	Cash Flow from Operations
CgbO	Cash generated by Operations
CMAD	Coefficient of the Median Absolute Deviation
CPY	Entity name
CV	Coefficient of Variation
DCF	Discounted Cash Flow
DGM	Dividend Growth Model
DPS	Dividend Per Share
E	Earnings
EBIT	Earnings Before Interest and Tax

Acronym/Abbreviation	Description
EBITDA	Earnings Before Interest, Tax, Depreciation and Amortisation
EBT	Earnings Before Tax
EPS	Earnings Per Share
EV	Entity Value
EVA	Economic Value Added
EY	Earnings Yield
FCF	Free Cash Flow
FCFE	Free Cash Flow to Equity
FCFF	Free Cash Flow to the Firm
FRE	Fraction Error
FRE 0.15	15% FRE
FRE 0.25	25% FRE
GAAP	Generally Accepted Accounting Practice
GP	Gross Profit
HE	Headline Earnings
IAS	International Accounting Standard
IBES	Institutional Brokers Estimation System
IC	Invested Capital
IFRS	International Financial Reporting Standards

Acronym/Abbreviation	Description
IMF	International Monetary Fund
IMP	Potential percentage improvement
IMP.SVC	IMP in the SVC
IMP.IVC	IMP in the IVC
IMP.PGV	IMP in the PGV
IND	Industry
IPO	Initial Public Offering
IQR	Interquartile Range
IVC	Industry Value Chain
JSE	JSE Securities Exchange
MAD	Median Absolute Deviation
Max	Maximum
MCap	Market Capitalisation
Min	Minimum
MPV	Market Price Variable
MVE	Median of the Valuation Errors
MVIC	Market Value of Invested Capital
N	Number of observations
NA	Insufficient data for analysis

Acronym/Abbreviation	Description
NASDAQ	National Association of Securities Dealers Automated Quotations
NCIfIA	Net Cash Inflow from Investment Activities
NCIfOA	Net Cash Inflow from Operating Activities
OD	Ordinary Dividends
P	Market Price per share
PAT	Profit After Tax
PBT	Profit Before Tax
PCA	Principal Component Analysis
PCR	Principal Component Regression
PEG	Price Earnings Growth
PGV	Peer Group Variable
PGVs	Peer Group Variables
Pre	Predicted
PwC	PricewaterhouseCoopers
P25	25th Percentile
P75	75th Percentile
R	Revenue
Rg	Revenue growth
RoA	Return on Assets

Acronym/Abbreviation	Description
RoE	Return on Equity
SAVE	Sum of the Absolute Valuation Errors
SD	Standard Deviation
SEC	Sector
SEC_1	Securities and Exchange Commission
SIC	Standard Industry Classification
SSVE	Sum of the Squared Valuation Errors
SUB	Subsector
SUP	Supersector
SVC	Sector Value Chain
TA	Total Assets
TIC	Ticker symbol
UK	United Kingdom
USA	United States of America
WACC	Weighted Average Cost of Capital

Used in formulae

Acronym/Abbreviation	Description
α_{it}	Actual value driver of entity i at time period t
b	Plough back rate
β	Beta weight
d	Debt
D_0	Current period's dividend (at point in time zero)
D_1	Next period's dividend (at point in time one)
$EBITDA_0$	Current period's EBITDA (at point in time zero)
$EBITDA_1$	Next period's EBITDA (at point in time one)
EPS_0	Current period's EPS (at point in time zero)
EV_0	Current period's EV (at point in time zero)
ε	Error term
$FCFF_0$	Current period's FCFF (at point in time zero)
$FCFF_1$	Next period's FCFF (at point in time one)
g_s	Stable growth rate
i	Entity i
K_c	Cost of capital

Acronym/Abbreviation	**Description**
K_e	Cost of equity
P_0	Current value of equity (at point in time zero)
r	Reinvestment rate, i.e. the proportion of operating profit that is re-invested in net capital expenditure and in working capital
t	Time period t
T	Tax rate
λ_t^e	Actual equity-based multiple at time period t
$\hat{\lambda}_{pt}^e$	Estimated equity-based peer group multiple at time period t
λ_t^n	Actual entity-based multiple at time period t
$\hat{\lambda}_{pt}^n$	Estimated entity-based peer group multiple at time period t
V_{it}^e	Actual equity value of entity i at time period t
$\hat{V}_{it}^e$	Equity value prediction of entity i at time period t

Industry-specific abbreviations

Acronym/Abbreviation	Description
BM	Basic Materials
CG	Consumer Goods
CS	Consumer Services
Fin	Financials
Ind	Industrials
Tec	Technology

Sector-specific abbreviations

Acronym/Abbreviation	Description
Ba	Banks
Be	Beverages
Che	Chemicals
C & M	Construction & Materials
E & EE	Electronic & Electrical Equipment
EII	Equity Investment Instruments
FS	Financial Services
F & DR	Food & Drug Retailers
FP	Food Producers
F & P	Forestry & Paper
GI	General Industrials
GR	General Retailers
IE	Industrial Engineering
IM & M	Industrial Metals & Mining
IT	Industrial Transportation
LI	Life Insurance
Me	Media
Mi	Mining

Acronym/Abbreviation	Description
MT	Mobile Telecommunications
NLI	Nonlife Insurance
PG	Personal Goods
P & B	Pharmaceuticals & Biotechnology
REI & S	Real Estate Investment & Services
REIT	Real Estate Investment Trusts
S & CS	Software & Computer Services
SS	Support Services
TH & E	Technology Hardware & Equipment
T & L	Travel & Leisure

CHAPTER 1

INTRODUCTION

1.1   BACKGROUND

1.1.1   The popularity of multiples

The field of valuations poses a major obstacle in emerging markets. In fact, it is the number one hurdle obscuring international investors' external growth initiatives into emerging markets (PricewaterhouseCoopers (PwC), 2012).[1] In a recent study by PwC (2012), in which 240 failed transactions in emerging markets were analysed, the range of potential outcomes was found to be significantly wider than for equivalent transactions in developed markets. The wider range is a reflection of the magnitude of the divide between the expectations of willing buyers and willing sellers.

Although equity valuations are approached quantitatively, the study thereof is not a precise science (Fisher, 2013; Correia, Flynn, Uliana & Wormald, 2011; Pratt, 2006; French & Gabrielli, 2004; Gabehart & Brinkley, 2002). A comparison between the values derived by the use of different valuation methods and the actual share price concerned attests to this (Yee, 2004; Lundholm & O'Keefe, 2001). Nevertheless, numerous researchers have endeavoured to determine which equity valuation methods are superior (Courteau, Kao & Richardson, 2001; English, 2001; Plenborg, 2001; Berkman, Bradbury & Ferguson, 2000; Francis, Olsson & Oswald, 2000; Hartman, 2000; Levin & Olsson, 2000; Biddle, Bowen & Wallace, 1999; Penman & Sougiannis, 1998). Given the various valuation methods available to investment practitioners, why is the focus in this dissertation on the relative valuation approach, which is also known as the market approach, or commonly referred to as multiples?[2]

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[1]   A complete list of acronyms/abbreviations is available in the TABLE OF CONTENTS section, while key variables are defined in Annexure A.

[2]   The term "investment practitioners" is used in a collective sense throughout this study. It includes, but is not limited to, equity analysts, investment bankers and asset managers.

Although investment practitioners may favour different valuation methods, they always employ multiples to some extent and almost always refer to multiples in their valuation reports (PwC, 2010; Damodaran, 2006b; Efthimios, Strong & Walker, 2004; Hendrikse & Hendrikse, 2004). Consequently, multiples are used extensively in practice (Roosenboom, 2007; Asquith, Mikhail & Au, 2005; Fernández, 2002), typically in conjunction with other valuation methods (Nel, 2010; Yee, 2004; Courteau, Kao, O'Keefe & Richardson, 2003; Bhojraj & Lee, 2002; Liu, Nissim & Thomas, 2002b; English, 2001; Hartman, 2000). In fact, Damodaran (2006b) argues that approximately 90% of valuations are relative valuations and 50% of acquisition valuations employ a combination of multiples and comparable entities. Damodaran (2009) points out that, in international markets, most assets are valued using the multiples approach. In a study of 550 equity research reports from United States of America- (USA), United Kingdom- (UK) and Asia-based investment banks in 2001, Damodaran found that multiples outnumbered Discounted Cash Flow (DCF) valuations by ten to one. Even when performing DCF valuations, terminal values are often based on multiples. Consequently, multiples are particularly prevalent in investment practitioners' reports and investment bankers' opinions (Schreiner, 2007) and find their way into various valuation-related reports. These reports include a multitude of corporate finance transactions, including valuations for Initial Public Offerings (IPOs), leveraged buy-outs, mergers and acquisitions, minority freeze-out bids and control premiums (Bates, Lemmon & Linck, 2006; Bhojraj & Lee, 2002; Graham & Lefanowicz, 1999).

The traditional multiples valuation approach assumes that the actual value of an entity's shares is equal to the product of a specific multiple and an accompanying value driver. Although, in theory, this may seem simple at first glance, there is an array of factors that complicate the application thereof. Do equity multiples and entity multiples yield similar results? Do multiples-based equity valuations produce reliable results in terms of valuation accuracy and, if so, which value drivers are superior? Other important considerations are whether the appropriate selection of comparable entities and industry-specific multiples improves valuation performance.

Despite these complications, the literature has been slow to provide guidance in this regard, especially in developing countries such as South Africa. International

research on corporate valuation practice focuses on the relatively deeply traded and liquid, developed markets in the USA and Europe, while shedding little light on emerging markets. The only international literature that offers a multiples framework in this regard was documented by Schreiner (2007), who focused on developing a framework for the application of multiples in developed countries in the USA and Europe. However, these findings cannot merely be extrapolated to other countries, particularly not in the case of developing countries with vastly different socio-economic and political characteristics (Barth, Beaver, Hand & Landsman, 2005).

1.1.2   An emerging market perspective

Despite international interest in how "best practitioners" value investments in emerging markets such as South Africa (Bruner, Conroy, Estrada, Kritzman & Li, 2002), the literature is silent on the need to develop a comprehensive multiples valuation framework, which addresses the factors mentioned in Section 1.1.1 above, in developing countries such as South Africa. According to Bruner *et al.* (2002), valuations are affected by factors such as liquidity, corruption, volatility and taxes, which differ in developing and developed markets. Investment inflows into emerging markets are significant, and improved valuation practices could significantly affect the welfare of investors. In addition, many emerging markets that are closely watched by international investors grow at real rates of over three times those of developed countries. Developing countries also account for large parts of the world population, land mass and natural resources.

However, despite these impressive growth expectations, international investors face various challenges when opting to invest in developing countries. African countries are no exception. Although each African country poses its own unique challenges, the generic issues relate to corruption, lack of infrastructure, trade barriers, an unproductive labour force and skills shortages. Not surprisingly, finalising deals in emerging markets is inherently riskier than in developed markets (PwC, 2012). Factors such as currency volatility, unreliable market measures and accounting differences come into play, all of which complicate valuations in emerging markets (Damodaran, 2009).

Although deals in emerging markets face the same generic obstacles as in developed markets, they differ significantly in terms of degree, frequency and root causes. The most prominent deal breaker in emerging markets is the inability of buyers and sellers to agree on valuations (PwC, 2012). The large gap in buyer and seller expectations can be traced to uncertainty regarding the magnitude of future growth, the availability of few comparable entities and strong competition for emerging market assets.

The limited availability of comparable entities is one of the key constraints to a multiples-based approach to valuations. The lack of truly comparable entities hampers the estimation of a peer group multiple and obscures objectivity. Similarly, adopting a comparable transactions approach is hampered by a lack of information, since the details of these transactions are rarely disclosed.

A significant number of valuations are performed for cross-border transaction purposes into Africa, with international interest from the USA, the UK and European investors (PwC, 2012). But what is it that Africa has to offer, in particular, and what are the challenges facing potential investors in Africa? Economic growth is generally the key factor when considering cross-border investments. Figure 1.1 and its underlying data contained in Table 1.1 provide a clear explanation for this.
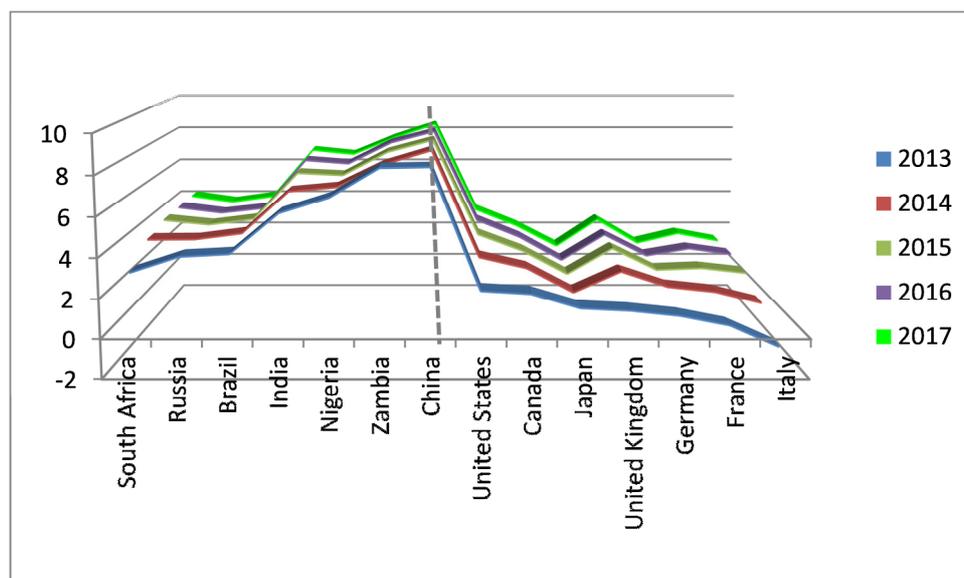
Figure 1.1: Five-year growth expectations
Source: International Monetary Fund (IMF) (2012)

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Table 1.1: Growth forecasts for the period 2013 to 2017

Groups/Countries	2013	2014	2015	2016	2017
Advanced economies (Including G-7 countries)	1.54%	2.28%	2.60%	2.65%	2.64%
Italy	-0.73%	0.50%	1.20%	1.40%	1.40%
France	0.37%	1.11%	1.48%	1.74%	1.86%
Germany	0.85%	1.37%	1.38%	1.33%	1.27%
United Kingdom	1.12%	2.18%	2.58%	2.55%	2.71%
Japan	1.23%	1.08%	1.15%	1.07%	1.09%
Canada	1.97%	2.37%	2.44%	2.43%	2.35%
United States	2.12%	2.94%	3.36%	3.41%	3.33%
Emerging market and developing economies	5.64%	5.90%	6.07%	6.14%	6.19%
South Africa	3.03%	3.86%	4.15%	4.15%	4.15%
Russia	3.82%	3.88%	3.90%	3.84%	3.80%
Brazil	3.95%	4.20%	4.20%	4.11%	4.14%
India	5.97%	6.39%	6.74%	6.89%	6.95%
Nigeria	6.74%	6.61%	6.63%	6.70%	6.70%
Zambia	8.19%	7.79%	7.90%	7.90%	7.70%
China	8.23%	8.51%	8.54%	8.54%	8.50%

Source: IMF (2012)

The vertical dotted line in Figure 1.1 separates the developed and developing countries, as defined by the IMF. As is evident from Figure 1.1, the major growth opportunities over the period 2013 to 2017 are expected to emanate from the developing countries. The supporting data contained in Table 1.1 indicates that, on average, growth in emerging market and developing economies is expected to outpace the advanced economies by 2.45 times over the period 2013 to 2017. Table 1.2 offers a similar comparison on a compound growth basis, which indicates similar results. From Table 1.2, it is equally evident why emerging markets are attracting so much attention from international investors. On a compound aggregate basis, emerging markets are projected to grow at 3.24 times the pace of developed markets over the period 2013 to 2017. This is based on a comparison between emerging market growth expectations and that of the G-7 countries. A comparison with advanced economies as a group (not shown here), which includes the G-7 countries, indicates a slightly lower projected growth rate of 1.95%, compared to the 2.00% of the G-7 countries, over the same period. Besides the allure of Brazil, Russia, India, China and South Africa (the BRICS countries), many African countries other than South Africa also offer exceptional growth opportunities. Two of South Africa's major trading partners, namely Zambia and Nigeria, are forecast to grow at 7.89% and 6.68%, respectively, over the period 2013 to 2017.

Table 1.2: Compound Annual Growth Rates (CAGRs) per country and on aggregate: 2013 to 2017

Major advanced economies (G7)		Emerging market and developing economies	
Country	CAGR	Country	CAGR
United States	3.03%	China	8.46%
Canada	2.31%	Zambia	7.89%
United Kingdom	2.23%	Nigeria	6.68%
France	1.31%	India	6.59%
Germany	1.24%	Brazil	4.12%
Japan	1.12%	South Africa	3.86%
Italy	0.75%	Russia	3.85%
Group	2.00%	Group	6.48%

Source: IMF (2012)

But what fuels these African economies? A major driving force of many African economies is the surging demand from China and other emerging markets for limited natural resources (Africa Progress Report, 2013). Africa's petroleum, gas and mineral resources have lured foreign investments and, based on global commodity market projections, will continue to do so, at least over the next decade. There are market investment practitioners who maintain that a period of sustained high commodity prices will be carried forward by a commodity super cycle (Africa Progress Report, 2013).

Therefore, given the strong investment drive into Africa and the popularity of multiples as a valuation approach, one would expect the construction of multiples to be supported by a strong theoretical base, underpinned by empirical evidence. Accounting and equity valuations are applied disciplines and, therefore, ultimately the aim of research in these fields should be to affect practice (Nissim & Penman, 2001). Unfortunately, international evidence suggests that investment practitioners and academia often seem to operate in isolation from each other, slightly suspicious of the value that academic rigour, on the one hand, and the pressures in the marketplace, on the other, might add to their respective approaches (Bernstein, 2008; Triantis, 2005; Ralston, 2003; Copeland, 2002). Similar research conducted in South Africa by Nel (2010; 2009b) indicates that a gap exists between theory and practice in the application of equity valuation and multiples, in particular. The lack of collaboration on the matter is not a new phenomenon either (Copeland, 2002; Smith

& Goudzwaard, 1970; Wendt, 1966; Upton, 1949). Consequently, opportunities exist to enhance multiples-based valuation theory and to converge academic thinking and issues encountered by investment practitioners in the market place.

These opportunities highlight the need for an empirical investigation into the factors that complicate the application of the traditional multiples valuation approach, as highlighted in Section 1.1.1 above. However, single factor multiples are constructed by scaling a single Market Price Variable (MPV) by a single matching value driver. Similarly, when employing multiples, investment practitioners typically consider each single factor multiple, in isolation. However, previous research by Schreiner (2007) indicated that, by combining different single factor multiples, one may be able to secure a more accurate valuation compared to the single factor multiples approach, i.e. composite multiples offer incremental valuation accuracy over the traditional single factor multiples valuation approach. Various international researchers have focused on combining earnings and book value multiples into a two-factor composite multiples model, which was found to enhance valuation accuracy (Chan, 2009; Henschke & Homburg, 2009; Schreiner, 2007; Cheng & McNamara, 2000; Penman, 1998). The validation of the research hypothesis, i.e. that composite multiples offer incremental valuation accuracy *vis-á-vis* single factor multiples in the South African market, hinges on the results obtained from the initial empirical investigation into the factors that complicate the traditional multiples valuation approach.

1.2   RESEARCH DESIGN

1.2.1   Research objectives

The fact that various multiples find their way into investment practitioners' reports seems to suggest that individual multiples carry incremental information. Therefore, the objective of the dissertation, which will be addressed in Chapter 9, is to establish whether combining single value estimates into an aggregate estimate will provide a superior value estimate *vis-á-vis* single value estimates, as hypothesised. A composite value estimate ensures that the incremental information is encapsulated in a superior value estimate and that biases and errors in individual estimates are averaged out.

Multi-factor modelling is not a new phenomenon in the financial literature. Ross (1976), for example, presents evidence that a two-factor arbitrage pricing theory model explains asset prices better than the traditional capital asset pricing model. Similarly, Fama and French (1996) document evidence in support of a three-factor capital asset pricing model that encapsulates many of the anomalies that are not explained by the traditional single factor capital asset pricing model. Although a multi-factor approach may not seem new in the field of finance, it is a novel application in respect of multiples-based valuations. International literature offers very little guidance in this regard and the evidence from emerging markets in particular, is limited in scope and seems rather lacklustre.

Consequently, prior to the development of optimal industry-specific composite models, one first has to understand what the proper construction of optimal single factor multiples entails. The latter requires empirical evidence in support of two key considerations: Firstly, the application of an optimal peer group selection strategy; and, secondly, the identification of two value relevant measures; namely the MPV and a matching value driver, which could be either equity-based or entity-based. Each of these components to the multiples-based valuation approach should be theoretically sound and empirically tested. To this end, five subordinate research questions must first be investigated, the results of which will direct the proper construction of optimal single factor multiples. These five research questions are contained in Figure 1.3. The empirical results obtained from Chapters 4 to 8 will present answers to these five research questions and verify the following five hypotheses, which are discussed in more detail in the specific chapters:

Hypotheses to research questions one to five:

H1: Multiples whose peer group selection is based on narrower industry classifications, i.e. smaller groups of more homogeneous entities, offer higher degrees of valuation accuracy *vis-á-vis* multiples whose peer group selection is based on wider industry classifications, i.e. larger groups of more heterogeneous entities.

H2:   Multiples whose peer group selection is based on a combination of valuation fundamentals, i.e. smaller groups of more homogeneous entities, offer higher degrees of valuation accuracy *vis-á-vis* multiples whose peer group selection is based on single valuation fundamentals, i.e. larger groups of more heterogeneous entities.

H3:   Equity-based multiples models offer higher degrees of valuation accuracy *vis-á-vis* entity-based multiples models.

H4:   Multiples models that are constructed on earnings-based value drivers offer higher degrees of valuation accuracy *vis-á-vis* multiples models that are constructed on asset-, revenue-, dividend- or cash flow-based value drivers.

H5:   The valuation accuracy of multiples is industry-specific, i.e. the optimal choice of value driver depends on the industry in which the target entity resides.

It is envisaged that the research results obtained from Chapters 4 to 8 will validate these five hypotheses and, in so doing, offer answers to research questions one to five (see Figure 1.3). The latter will create a theoretical platform for the construction of optimal single factor multiples models, which will subsequently be compared to industry-specific composite multiples models in Chapter 9. The aim of this comparison is to validate the main research hypothesis, which posits the following:

H6: Industry-specific composite multiples models offer higher degrees of valuation accuracy *vis-á-vis* industry-specific single factor multiples models.

The validation of H6 will present an answer to research question six (see Figure 1.3), which will aid the development of optimal industry-based composite multiples models for the purpose of valuing the equity of South African entities that are listed on the JSE Securities Exchange (JSE). However, in order to develop a set of optimal composite multiples models, the research hypothesis must first be validated, i.e. an empirical investigation is required to determine whether equity valuations based on industry-specific composite multiples outperform valuations based on industry-specific single factor multiples in terms of valuation accuracy. The research

hypothesis, stipulated in H6, therefore aims to establish whether composite-based multiples improve on the valuation accuracy of single factor multiples.

1.2.2   Contribution of the research

The literature review highlighted various shortcomings in the current emerging market literature on multiples-based valuation theory, particularly in the South African context. The verification of the six research hypotheses stipulated in Section 1.2.1 will enhance current multiples-based valuation theory in South Africa. Similarly, numerous misconceptions and misapplications of multiples-based valuation theory exist in practice in South Africa, which may in future be regulated to a greater extent. The research findings offer empirical support for the application of multiples-based valuation theory. As such, this study makes various contributions to the literature on multiples-based valuations in emerging markets and, in particular, in the context of corporate valuation practice in the South African market:

- This is the first comprehensive study on the construction of composite multiples models in South Africa. There is only one documented study on composite modelling in emerging markets, which, among other discrepancies, was conceptually flawed, limited in scope and produced contradictory results. All the other previous studies focused on the relatively deeply traded and liquid markets in the USA and Europe, while shedding little light on emerging markets.

- Contrary to most existing international studies, this study considers five different types of composite variables, namely earnings, assets, revenue, dividends and cash flow; and 16 different potential variables. In previous studies, the number of variables contained in the composite models was largely limited to two, namely the P/EPS ratio (P refers to Market Price per share and EPS refers to Earnings Per Share) and the P/BVE ratio (BVE refers to Book Value of Equity.

- Most existing studies compared composite multiples models with single factor multiples models only, since an inter-composite comparison in a two-factor composite model is nonsensical.

- This study tests the weightings of the components contained in the composite models, whereas many of the previous studies limited their research to equally-weighted composites.

- This study develops optimal composite models for all industries for which sufficient data is available.

- The study highlights various misconceptions and misapplications regarding multiples in the South African market.

- This study is the first to employ Principal Component Analysis (PCA) to composite multiples modelling, effectively reducing the multi-dimensional nature of the data and aiding the analysis thereof. A novel technique, in the form of PCA biplots, is used to display common trends and patterns in the data over time.

- A total of 32 functions were developed in *R-code*, an open-source programming language that lends itself to statistical analysis and graphics (R Core Team, 2013). These functions assisted with the preparation of the data, the measurement and analysis of the valuation accuracy of the 16 multiples and the optimisation of the composite weightings. A list of these functions is summarised in Annexure C, while the relevant *R-code* is shown in Annexure D. Note that these functions are generic. They are, therefore, not only applicable to the specific data set applied in this study, but can also be applied to a different data set in other studies.

- Errors in the McGregor Bureau of Financial Analysis (BFA) database were detected and communicated to the entity for correction.

1.3   RESEARCH OUTLINE

Figure 1.2 offers a graphical illustration of the research outline of the dissertation. Chapter 2 presents the theoretical basis of the dissertation and Chapter 3 provides the research methodology and data selection and analysis process. In order to validate the six research hypotheses, a fair amount of data preparation was required before the data could be used. To this end, various functions were written in *R-code*, which accommodated data preparation for both this study and future research efforts in this regard. Refer to Annexures C and D for the detail of these functions.

Figure 1.3 presents an outline of the empirical research in relation to the six research questions, for which the hypotheses and findings are offered in Chapters 4 to 9. Each of these chapters contains an international and South African literature review in order to ascertain the nature of existing research regarding research questions one to six. The aim is to reflect that, although multiples have been the topic of a number of international research attempts over the past decade, a considerable gap exists in the literature in terms of multiples-specific research in developing countries such as South Africa. A cross-sectional analysis is conducted in Chapters 4 to 7 to verify research hypotheses one to four and, in so doing, to answer research questions one to four. This is followed by an industry analysis, which is conducted in Chapters 8 and 9 to verify the research hypotheses contained in research questions five and six. A conclusion and summary of the main findings are offered in Chapter 10, together with a synopsis of implications for practice and caveats that may present potential future research opportunities. Following the graphical illustration of the dissertation's layout, as provided in Figures 1.2 and 1.3, is a short summary of the chapters contained in the dissertation.
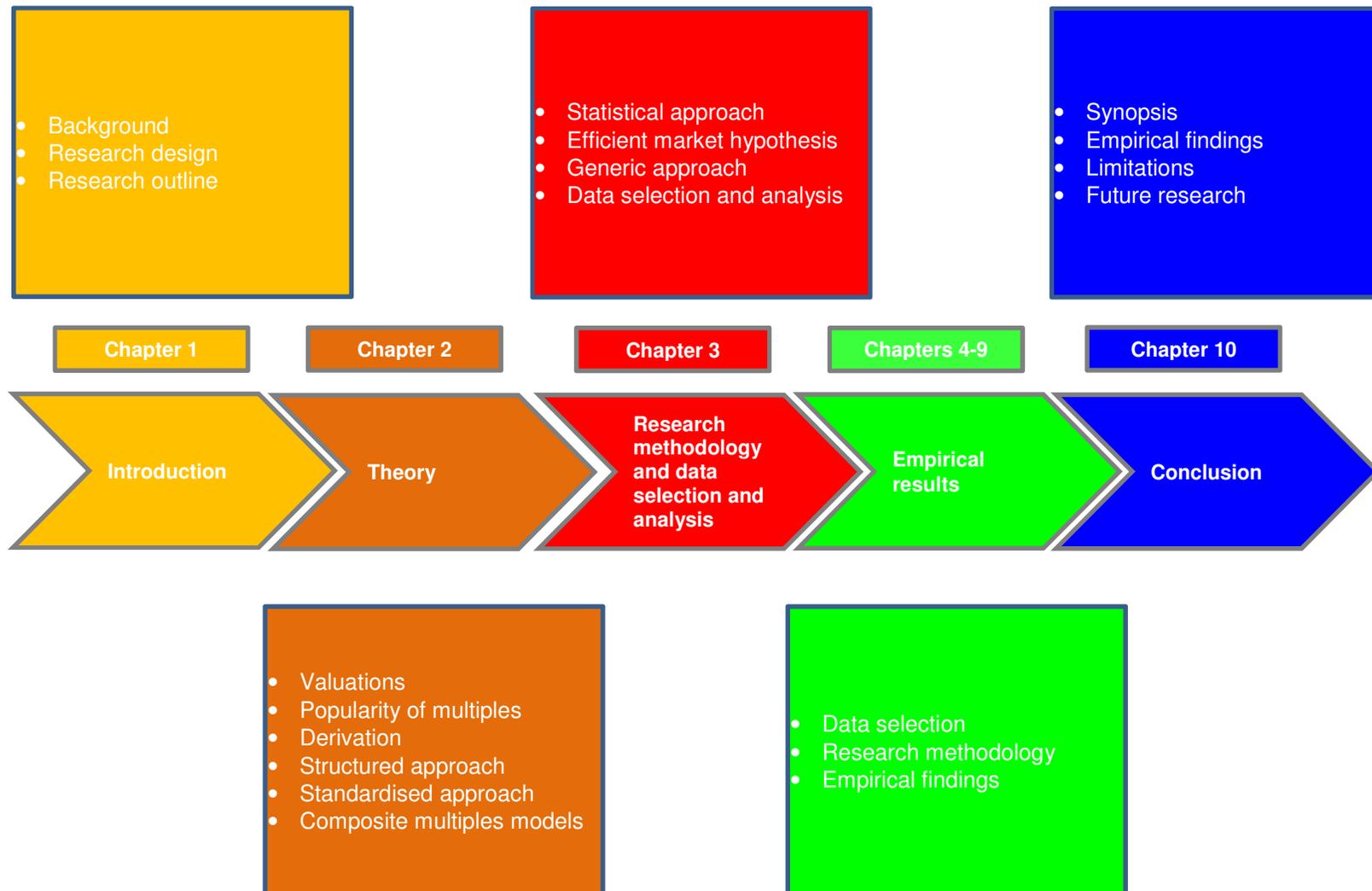
Figure 1.2: Outline of the research

Chapter 9

Research Question 6
Do industry-specific composite multiples models improve the valuation accuracy of industry-specific single factor multiples models?

- ❖ Composite models versus single factor multiples
- ❖ Industry-based valuation performance
- ❖ Precision and consistency

Chapter 8

Research Question 5
Do industry-specific multiples improve the valuation accuracy of multiples?

- ❖ Optimal peer group selection basis
- ❖ Industry-based valuation performance
- ❖ Sector Value Chain

Chapter 7

Research Question 4
Which value drivers offer the greatest degree of valuation accuracy among single factor multiples?

- ❖ Value driver categories
- ❖ Individual value drivers
- ❖ Precision, consistency and bias

Chapter 6

Research Question 3
Do equity-based multiples produce more accurate valuations than entity-based multiples?

- ❖ Descriptive statistics: Central tendency
- ❖ Descriptive statistics: Dispersion

Chapter 5

Research Question 2
Does peer group selection based on economic fundamentals improve the valuation accuracy of multiples?

- ❖ Descriptive statistics: Central tendency
- ❖ Descriptive statistics: Dispersion
- ❖ Valuation accuracy of valuation fundamentals
- ❖ Peer group selection

Chapter 4

Research Question 1
Do narrower industry classifications improve the valuation accuracy of multiples?

- ❖ Descriptive statistics
- ❖ Impact of industry classification

Figure 1.3: Outline of empirical research

Chapter 2: Theoretical background

The theoretical background offered in Chapter 2 highlights the importance and popularity of multiples-based valuations, especially on the African continent. Multiples-based models are derived from DCF-analysis to illustrate that these two valuation approaches are underpinned by the same economic fundamentals. Section 2.4 stresses the importance of adopting a structured approach when employing multiples to conduct valuations. This is followed by the standard multiples-based valuation approach and its limitations in Section 2.5, which facilitates an understanding of the main constituents of multiples. Section 2.5 provides an extension of the existing theoretical basis for employing multiples for valuation purposes. The traditional four-step multiples valuation process is presented as a backdrop to the identification of the intricacies involved when performing valuations based on multiples that require further research. Accordingly, the six research questions originate from the lack of clarity in the traditional multiples approach, as illustrated in this chapter. The final Section offers the theory underpinning the concept of composite multiples models.

Chapter 3: Research methodology and data selection and analysis

In Chapter 3 the general research methodology that is employed to answer the six research questions is clarified. Different methodologies will be employed for single factor- and composite multiples models. The data selection and analysis process and final data set are also discussed.

Chapter 4: The impact of industry classification-based peer group selection on the valuation accuracy of multiples

The valuation accuracy of multiples depends largely on the selection of a comparable entity set (peer group). Consequently, the impact of peer group selection by way of industry classification is investigated by assessing the valuation performance of multiples over various industry classifications, as defined by the JSE.

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To this end, the industry classification system on the McGregor BFA database, i.e. Industry (IND), Supersector (SUP), Sector (SEC) and Subsector (SUB) is tested for valuation accuracy. The premise is that peer group selection based on a narrower industry classification should increase the valuation accuracy of multiples. The aim of this investigation is to answer research question one, i.e. to establish whether narrower industry definitions improve the valuation accuracy of multiples.

Chapter 5: The impact of valuation fundamentals-based peer group selection on the valuation accuracy of multiples

The focus in Chapter 5 is on peer group selection based on entities with similar valuation fundamentals, i.e. entities with similar risk, growth and profitability profiles. The impact of peer group selection based on three valuation fundamentals, or, combinations thereof, is investigated by assessing the valuation performance of the multiples whose peer groups are based on these valuation fundamentals. The premise is that multiples whose peer groups are based on a combination of valuation fundamentals should offer a greater degree of valuation accuracy *vis-á-vis* multiples whose peer groups are based on single valuation fundamentals. The aim is to answer research question two, i.e. to establish whether peer group selection based on a careful selection of valuation fundamentals may improve the valuation accuracy of multiples.

Chapter 6: The valuation performance of equity- and entity-based multiples

Investment practitioners typically distinguish between equity- and entity-based approaches when employing the Free Cash Flow (FCF) model to perform equity valuations. However, when multiples are used to perform equity valuations, investment practitioners often neglect to distinguish between equity- and entity-based approaches. Consequently, Chapter 6 explores whether empirical evidence supports the notion that either equity- or entity-based multiples deliver superior valuation results, i.e. in terms of valuation accuracy, compared to the other. The results of this research will provide an answer to research question three. Depending

on the outcome of this investigation, the remainder of the research will focus on either equity- or entity-based multiples.

Chapter 7: The valuation performance of value drivers

The relative valuation performance of 16 value drivers is tested on a per category basis and on an individual value driver basis. The 16 value drivers are selected from five different value driver categories, namely earnings, assets, revenue, dividends and cash flows. The precision and consistency of their relative valuation performance are investigated over time in order to answer research question four, i.e. when employing single factor multiples, which value drivers offer the greatest degree of valuation accuracy? The tendency of multiples based on these 16 value drivers to over- or underestimate the market is also investigated, to test for the presence of downside or upside bias.

Chapter 8: Industry-specific multiples

While a cross-sectional analysis was conducted in Chapters 4 to 7, an industry analysis approach is adopted in Chapters 8 and 9. The aim of Chapter 8 is to answer research question five by investigating whether empirical evidence exists to support the common practice of using industry-preferred multiples. Apart from establishing whether such preferences are warranted, it is also envisaged that different peer group selection methods may be best suited to different industries. Consequently, the 10 peer group selection methods discussed in Chapters 4 and 5 are revisited on a per industry basis in order to ascertain which peer group selection methods are best suited to which industries.

Chapter 9: The valuation performance of composite multiples models

The analyses in Chapters 4 to 8 provide a theoretical foundation for the construction of industry-specific composite multiples models. The purpose of Chapter 9 is to

ascertain whether equity valuations based on industry-specific composite multiples models outperform equity valuations based on the industry-specific single factor multiples models in terms of valuation accuracy and, ultimately, to develop optimal industry-specific composite multiples models for performing equity valuations of listed South African entities. To this end, guidance will be gleaned from the empirical results of Chapters 4 to 8.

Chapter 10: Conclusion

Final conclusions are drawn on the development of optimal industry-specific composite multiples models based on the empirical results obtained from Chapters 4 to 9. Since this study does not present an exhaustive analysis of all the potential research avenues on the topic of multiples, caveats are highlighted and presented as catalysts for potential future research topics.

CHAPTER 2

THEORETICAL BACKGROUND

2.1   VALUATIONS

A PwC valuation methodology field survey, which was conducted among 38 leading financial investment practitioners and corporate financiers in Southern, East and West Africa in 2012, provides valuable insight regarding the equity valuation approaches that are applied most frequently in practice (PwC, 2012). Refer to the list of respondents, as contained in Annexure B. Various types of questions were posed to the respondents. Among them were frequency-type questions, where the respondents were asked to indicate how frequently they adopted a certain methodology. The 2012 PwC survey results were represented in a frequency table, from which a scale between 3 and 0 was derived, where 3 indicated that the method is always used, 2 indicated the method is frequently used, 1 indicated that the method is sometimes used and 0 indicated that the method is seldom or never used. The most popular valuation approaches that are currently used in practice in Southern Africa, according to the PwC survey, are illustrated in Figure 2.1.

From the four valuation approaches depicted in Figure 2.1, it is evident that the two most popular valuation approaches in Southern Africa are the Income approach (DCF) and Market approach (multiples) (PwC, 2012). These findings are in line with the findings of the previous PwC survey, pertaining to South Africa in particular, which was conducted in 2010 (PwC, 2010). Although Figure 2.1 reflects the popularity of the four valuation approaches in Southern Africa, these four valuation approaches are equally popular in developed markets (Dellinger, 2010; Pratt & Niculita, 2007; Gabehart & Brinkley, 2002).

However, investment practitioners hold opposing views on the suitability and merits of the DCF and multiples approaches. Private equity and venture capitalist practitioners may prefer a multiples-based approach, based on observable market

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data rather than assumption-driven modelling (International Private Equity and Venture Capital Guidelines, 2010).
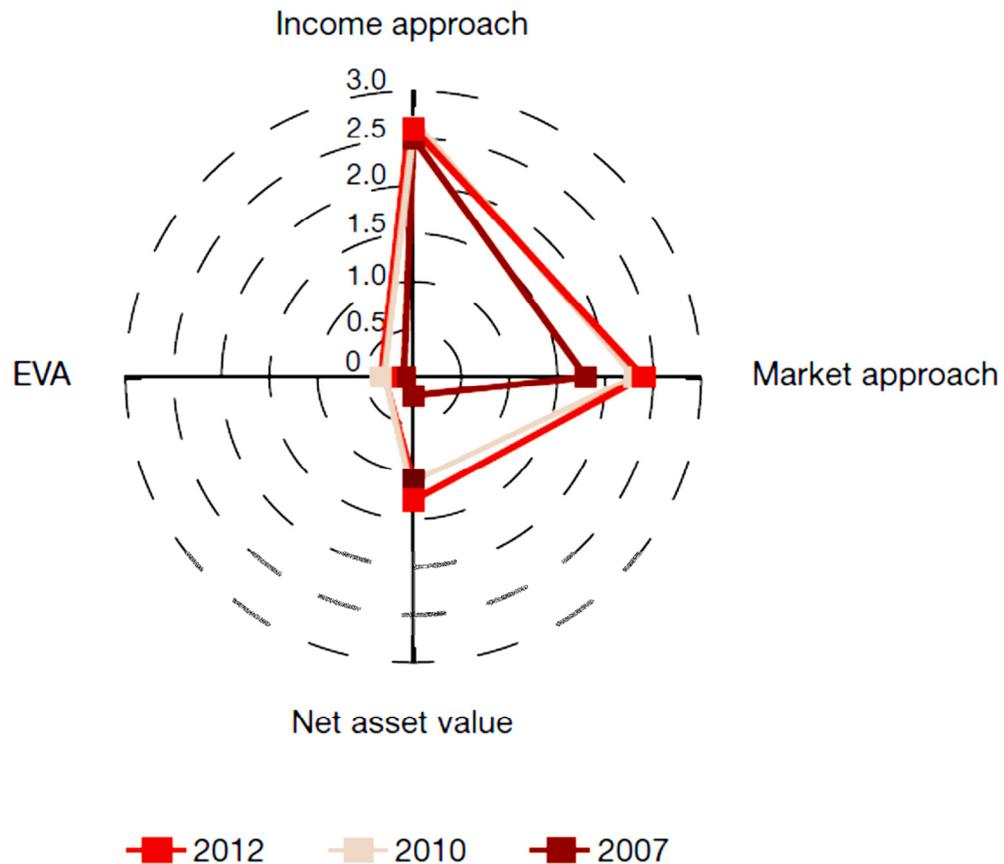
Figure 2.1: Valuation approaches
Source: PwC (2012)

At the other end of the spectrum, DCF proponents may argue that the limited depth and breadth of emerging markets such as South Africa necessitate a more robust DCF approach. A multiples-based approach to equity valuations is hampered by two caveats. Firstly, the availability of directly comparable entities with similar risk and growth profiles to that of the target entity is limited. Secondly, multiples-based valuations are extremely susceptible to the volatility of the stock market, which is driven by changes in investor sentiment.

Alternatively, a DCF approach affords one the opportunity to carefully consider the target entity's specific risk and growth profile and therefore offers a more thorough analysis of the target entity's longer-term value. In DCF valuations, the intrinsic value

of an asset is based on its ability to generate future cash flows, given its risk and growth characteristics. Multiple valuations, on the other hand, are based on judgments about the value of an asset in comparison with what the market is willing to pay for similar assets (Damodaran, 2009). This would imply that a large degree of trust is vested in the market for the determination of accurate valuations, at least on average. If such trust is warranted and the market, on average, is correct, DCF valuations and multiple valuations may actually converge (Damodaran, 2009). However, if the market systematically misprices certain assets or industries, DCF-based valuations will diverge from multiples-based valuations.

According to Damodaran (2009) most assets in international markets are valued using the multiples approach, which explains why investment practitioners' reports and investment bankers' opinions typically include multiples-based valuations (Schreiner, 2007). Investment practitioners also often refer to multiples-based rules of thumb when identifying investment opportunities. Shares trading at P/EPS ratios below their expected growth rates, for example, are regarded as good buys. This raises the question as to why multiples are so popular in practice, if DCF modelling is regarded as a more robust approach to equity valuations *vis-à-vis* multiples modelling?

2.2   THE POPULARITY OF MULTIPLES: USES AND ABUSES

The first and most obvious answer for the popularity of multiples lies in their simplicity. A multiples-based valuation does not require sophisticated calculations regarding the estimation of an entity's cost of capital and future free cash flows, which may prove quite a cumbersome exercise. This is especially difficult for young or entrepreneurial entities employing innovative new business models. A view must be taken regarding a number of disparate future variables. What will constitute an appropriate long-term growth rate and operating margin? Will the entity be able to maintain its competitive advantage and stifle competition; and for how long? It is precisely the uncertainty of these inputs that causes investment practitioners to revert to multiples, which merely rely on the market's assessment of the value of other entities with similar prospects.

This, in turn, leads to a second advantage – a multiples-based approach is based on actual prices of actual entities, rather than on future cash flow forecasts, which may prove unrealistic (Berk & DeMarzo, 2007; Kamstra, 2003).

Thirdly, the use of multiples is less time and resource consuming than the DCF approach. The DCF approach requires far more information than a multiples-based approach, which is why investment practitioners who are faced with time constraints and limited information often revert to multiples.

Fourthly, investment practitioners may find it easier to sell shares to potential investors based on a multiples-based valuation rather than on a DCF-based valuation. An investment practitioner or his/her marketing assistant will have to invest significantly more time in a sales pitch to their prospective investors when selling a DCF-based valuation *vis-á-vis* a multiples-based valuation. In short, delivering a share sales pitch with a DCF-based valuation as substantiating support is far more time consuming than a multiples-based sales pitch.

Fifthly, multiples-based valuations are market-based. DCF valuations are based on an array of assumptions, which may be difficult to defend when under scrutiny from clients or potential investors. Multiples, however, are based on what the market is willing to pay for similar assets. Consequently, if multiples are based on information that is obtained from the financial markets, this implies that they contain significant value relevant information content, which investors can use for valuation purposes (Eberhart, 2001). Refuting these values seems futile as it reflects an attack on the market itself.

Lastly, multiples are essentially relative valuations and, therefore, should reflect the current mood of the market more accurately than DCF valuations. This is borne from the fact that relative valuations, by definition, imply that a share is valued relative to the value of similar shares in the same industry, for example, and are not necessarily based on intrinsic value (Damodaran, 2009).

Unfortunately, many of these strengths are accompanied by risks. Multiples estimate the value of an asset by using a comparable asset price ratio as a benchmark in

relation to a common variable, such as earnings or revenue. Many investment practitioners calculate an industry average multiple and multiply it by the target entity's earnings or revenue, for example, to value the target entity's equity (Goedhart, Koller & Wessels, 2005). The starting point is typically the identification of a benchmark multiple of a similar listed entity in the same industry, or the calculation of the average of that multiple for the industry in which the target entity operates. The value of equity is therefore approximated by studying the market values of a peer group of entities. The value of equity is then calculated by multiplying the peer group multiple with the value driver of the target entity.

The first point of criticism against multiples pertains to their construction bias. The ease with which multiples can be constructed from a selected comparable entity set could lead to inconsistent values if the valuation fails to take account of inter-company differences in risk, earnings growth and cash flows. In fact, an investment practitioner who is free to perform a valuation based on any multiple and comparable entity set that he/she selects, may ensure that a certain, biased value is obtained.

Secondly, aside from the risk of construction bias, the selection of a comparable entity set rests partly on the underlying assumption that entities constituting the peer group are actually comparable to the target entity. Although similar assets should have similar values, in an efficient market at least, similar entities are often difficult to identify. Reasons for the difficulty in identifying peer group multiples range from the fact that very few entities, if any, have similar operational and financial characteristics; to differences in accounting treatment or market mispricing (Schreiner, 2007).

Thirdly, multiples assume that the market, on average, prices the comparable entities correctly. The fact that multiples may better reflect the current mood of the market may result in over- or undervaluations, depending on whether the market over- or undervalues comparable entities at the time (Damodaran, 2009).

However, regardless of their limitations, multiples can be, and are, used extensively in practice to obtain an approximation of market values attached to particular shares or entities. Despite the opposing views of investment practitioners, DCF modelling

and multiples modelling are remarkably well linked. In fact, when analysing the fundamentals of DCF- and multiples-based modelling, one discovers that multiples can be derived from DCF-based modelling.

2.3   DERIVING MULTIPLES-BASED FORMULAE FROM DCF-BASED MODELLING

DCF-based modelling determines the value of an entity, or its equity, as a function of three key variables, namely cash flow generating capacity, the expected growth rate in these cash flows and the risk associated with these cash flows (Damodaran, 2006a). Although the actual measures employed for these three key variables may vary among different multiples, the same three variables drive multiples, regardless of the choice of value driver. The cash flow generating capacity and the expected growth rate have a positive relationship with the size of multiples, while risk holds a negative relationship with the size of multiples.

In theory, therefore, one should be able to derive multiples from DCF-based modelling. For example, the simplest form of an equity-based DCF model is probably the stable Dividend Growth Model (DGM).[3]

$$P_0 = \frac{D_1}{K_e - g_s}$$
(2.1)

where

P_0 = Current value of equity (at point in time zero)

D_1 = Next period's dividend (at point in time one)

K_e = Cost of equity

g_s = Stable growth rate

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[3]   Although the DGM is generally classified as a dividend-based model, it is essentially also based on cash flows in the form of dividends.

Bear in mind that:

$$D_1 = D_0 \left(1 + g_s\right)$$
(2.2)

where

$D_0 =$ Current period's dividend (at point in time zero)

From Equation (2.1), therefore, one can derive, for example, the P/EPS multiple for a stable growth entity by dividing both sides by current EPS:

$$\frac{P_0}{EPS_0} = \frac{\left(1 - b\right)\left(1 + g_s\right)}{K_e - g_s}$$
(2.3)

where

$\dfrac{P_0}{EPS_0}$ = Current period's P/EPS multiple (at point in time zero)

EPS_0 = Current period's EPS (at point in time zero)

b = Plough back rate

From Equation (2.3) one can identify the valuation fundamentals of the P/EPS multiple, namely the pay-out ratio, the expected growth rate and the cost of equity. While the first two fundamentals will have a positive relationship with the P/EPS multiple, the latter will have a negative relationship, i.e. a higher pay-out ratio and expected growth rate; and a lower cost of equity, will culminate in a higher P/EPS multiple. The derivation of Equation (2.3) affords one the opportunity to understand the variables that cause multiples to vary across entities in the same sector (Damodaran, 2006a). One can apply similar logic to derive equity-based multiples for other value driver categories, i.e. dividends, assets, cash flow and revenue.[4]

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[4] For a detailed analysis in this regard see Damodaran (2006a).

The same reasoning can be applied to derive entity-based multiples. The simple equation for calculating the Entity Value (EV) of a stable growth entity based on a Free Cash Flow to the Firm (FCFF) analysis, is as follows:

$$EV_0 = \frac{FCFF_1}{K_c - g_s}$$

(2.4)

where

EV_0 = Current period's EV (at point in time zero)

$FCFF_1$ = Next period's FCFF (at point in time one)

K_c = Cost of capital

g_s = Stable growth rate

FCFF is regarded as free since it can be withdrawn from the entity without adversely affecting entity operations. Consequently, FCFF is calculated after entity taxes and the entity's reinvestment needs have been taken into account, i.e. FCFF equates to Earnings Before Interest, Tax, Depreciation and Amortisation (EBITDA), after tax minus net capital expenditure and investment in working capital.[5]

Bear in mind that FCFF can be rewritten in terms of operating profit (EBITDA), so that:

$$FCFF_1 = EBITDA_1 (1 - T)(1 - r)$$

(2.5)

where

$EBITDA_1$ = Next period's EBITDA (at point in time one)

---

[5]   Note that, in order to arrive at the purest form of FCFF, one should also adjust EBITDA for non-cash items such as provisions and one-off incidences that are unlikely to reoccur. However, the objective here is to identify the main determinants of the EV/EBITDA multiple and these adjustments will not alter the nature of these determinants.

T = Tax rate

r = Reinvestment rate, i.e. the proportion of operating profit that is re-invested in net capital expenditure and in working capital

and that:

$$FCFF_1 = FCFF_0\left(1 + g_s\right)$$ (2.6)

where

$FCFF_0$ = Current period's FCFF (at point in time zero)

Therefore, from Equation (2.4) one can derive, for example, the EV/EBITDA multiple for a stable growth entity by dividing both sides by current EBITDA:

$$\frac{EV_0}{EBITDA_0} = \frac{\left(1-T\right)\left(1-r\right)\left(1+g_s\right)}{K_c - g_s}$$ (2.7)

where

$\dfrac{EV_0}{EBITDA_0}$ = Current period's EV/EBITDA multiple (at point in time zero)

$EBITDA_0$ = Current period's EBITDA (at point in time zero)

From Equation (2.7) one can identify the valuation fundamentals of the EV/EBITDA multiple, namely the reinvestment rate, expected growth rate and the cost of capital. While the expected growth rate will have a positive relationship with the EV/EBITDA multiple, the reinvestment rate and the cost of capital will have a negative relationship with the multiple, i.e. a higher expected growth rate; and a lower reinvestment rate and cost of capital, will culminate in a higher EV/EBITDA multiple. One can apply similar logic to derive entity-based multiples for other value driver categories, i.e. assets, dividends, cash flow and revenue.

Deriving multiples from DCF modelling affords one the opportunity to isolate the valuation fundamentals that drive these multiples, which, in turn, facilitates a comprehensive cross-sector comparative analysis. Failure to conduct a careful analysis of these fundamentals may result in incorrect investment decision making. For example, when comparing two investment alternatives, one with a P/EPS multiple of 6 and another with a P/EPS multiple of 10, one may, incorrectly, conclude that the entity with a P/EPS multiple of 6 offers good value relative to the entity with a P/EPS multiple of 10, while the latter may simply be expecting a higher growth rate. Therefore, it is imperative that due care is taken to follow a structured approach when constructing multiples.

2.4   A STRUCTURED APPROACH TO THE USE OF MULTIPLES

The following four guidelines may help to preserve the integrity of multiples when performing equity valuations (Damodaran, 2006a):

- Define the multiples consistently and measure them uniformly across all the entities being compared.
- Take cognisance of the distributional characteristics of the multiples.
- Ensure a thorough understanding of the fundamentals that underpin the multiples, i.e. understand what drives the multiples.
- Identify the right peer group of entities and control for differences among the entities in the peer group.

Given the importance of these four guidelines, further consideration is warranted.

2.4.1   Consistency and uniformity

As mentioned in Chapter 1, the main reason that negotiations regarding emerging market transactions fail is valuation discrepancies. Different investment practitioners, especially buy-side and sell-side investment practitioners, will not necessarily define multiples in the same way. The P/EPS ratio, for example, is calculated by dividing P by EPS. Although investment practitioners typically use the current market price as the numerator, it is also feasible to use the average market price over the past year,

for example. Similarly, EPS can be calculated based on historical or forward earnings and the per-unit calculation can be based on the weighted average number of shares in issue or fully diluted shares in issue. Therefore it is important to use a consistent definition for multiples to ensure a comparable basis when valuation discrepancies arise.

The choice of numerator and denominator may depend on the view of the investment practitioner pitching a sale. Buy-side investment practitioners with a bullish view of future earnings may focus on the forward P/EPS ratio since rising earnings will orchestrate a lower P/EPS ratio, supporting their case that the share offers good value. Sell-side investment practitioners with a bearish view of the market may choose to focus on the current P/EPS ratio to support their case that the share is fully priced. Consequently, a consistent definition of multiples is required to ensure non-biased valuations and to facilitate comparison.

A consistency check should also be performed between a multiple's Market Price Variable (MPV), the numerator, and its value driver, the denominator. If an equity-based MPV is used, the value driver should also be equity-based and *vice versa* for entity-based valuations. The P/EPS ratio construct, for example, has a consistently defined combination of an MPV and value driver since both these variables constitute equity values. Similarly, at an entity level, the MVIC/EBITDA multiple (MVIC refers to the Market Value of Invested Capital) is a consistently defined multiple since both variables reflect entity values. However, mixing equity and entity measures results in inconsistently defined multiples, which may lead to incorrect valuations. The P/EBITDA multiple, for example, comprises an equity-based MPV, P, and an entity-based value driver, EBITDA. Since MVIC, the more correct MPV in this case, is substituted for P, which excludes the market value of debt, the numerator is lower. This will result in artificially lower valuations of shares for entities with significant levels of debt on their statements of financial position *vis-à-vis* entities with insignificant levels of debt. Consequently, even if the multiple is calculated in the same manner for all the comparable entities, the valuations will be incorrect.

Therefore, when specifying any multiple, the correct definition should be uniformly applied to all the entities in a specific group. For example, if the decision is taken to

use the 12-month trailing P/EPS ratio, this specification should be applied across the board. Careful consideration should also be given to differences in the accounting treatment of variables such as earnings and book value, for example. The earnings-based multiples of entities that follow a more aggressive approach when measuring earnings may appear more affordable than those of entities that adopt more conservative accounting approaches (Damodaran, 2006a).[6]

2.4.2 Distributional characteristics

The most important properties that are usually included in the descriptive analysis of a data set are the central tendency, dispersion and skewness. The central tendency of the data set refers to the centre of the distribution of data points. The mean and the median are the most commonly used measures in describing the central tendency of a data set. If a data set is symmetric, then both the median and the mean of the data set coincide with each other. However, the mean is influenced by outliers. Consequently, in the presence of outliers the mean will not provide an accurate reflection of the central tendency of the data set, in which case, the median will serve as a better measure of central tendency. Due to the mean's susceptibility to outliers, most researchers have a preference for the median, which is not affected by the presence of outliers.

Dispersion refers to the spread of data around the centre of the distribution, as reflected by the mean or the median, for example. Popular measures in this regard are the Standard Deviation (SD), Coefficient of Variation (CV), Interquartile Range (IQR), Median Absolute Deviation (MAD), and the Coefficient of the Median Absolute Deviation (CMAD).

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[6]   Although not specifically aimed at eliminating these differences in accounting conventions, the McGregor BFA databases devised a standardised system of analysing and capturing the financial statements of entities, which accommodates comparison. This is contained in a subset of the database known as the standardised accounting database, which converts the published financials into comparable financials across the board.

A perfect symmetric distribution of a data set, such as a normal distribution, is very seldom, if ever, found when analysing multiples. Whereas a distribution that exhibits significant positive skewness has a long right tail, a distribution with significant negative skewness has a long left tail.

A fourth property that is often included in the descriptive analysis of a data set, is its kurtosis. Kurtosis refers to the extent to which observations cluster or peak around a central point or, more specifically, it is a measure of the height of the distribution around a central point. Evidently, no such clustering will be found in a normal distribution, but, as mentioned above, this seldom, if ever, occurs when analysing multiples. Positive kurtosis indicates that the observations cluster more and have longer tails than those in the normal distribution, while negative kurtosis indicates less clustering and shorter tails.

Investment practitioners generally have a good grasp of the distributional characteristics of multiples within specific sectors of the market, which helps them determine which shares are over- or undervalued within specific sectors (Damodaran, 2006a). However, a careful statistical analysis may often be lacking. Multiples that are negative, for example, are often omitted because they are nonsensical, which allows for an upward bias in the distribution of values. Limiting the lowest multiples values to zero, while placing no limit on the higher multiples values, results in positively skewed data. Consequently, the mean multiple for a specific sector will be above the sector's median multiple. Therefore, investment practitioners who recommend a share as a buy because the multiple is below the mean for the specific sector may well be overstating their case. The consequences of these asymmetric distributions may be significant. In this case, the median multiple may be more representative of the typical entity in the group, which necessitates comparison to the median and not the mean. Alternatively, the harmonic mean can be used as an averaging procedure or various percentiles can be used to determine low and high multiple values for a specific group of entities.

An important consideration in this regard is the treatment of outliers. This is especially relevant when investment practitioners use data published by publishing services such as Bloomberg, McGregor BFA, etc. It is therefore imperative that

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investment practitioners who use these services are cognisant of the methodology applied to calculate multiples, especially regarding the treatment of outliers among these multiples, to ensure consistency in their comparisons.

A further consideration when applying multiples is that they do not remain constant over time. Consequently, comparing multiples over time may be a risky exercise since the reliability of these multiples may be short-lived. The important factor to consider is the shift in the underlying fundamentals that brought about the change in the multiples. Recessionary times, such as the period following the 2008 collapse of the housing market in the USA and the ensuing credit crisis, saw multiples decrease significantly. EV/EBITDA multiples, for example, in South Africa and Egypt, the two countries possessing the highest quality stock exchanges in Africa, declined from 11 in mid-2007 to 4 in early 2009, and from 13 in mid-2008 to 6 in early 2009, respectively (RisCura Fundamentals Analysis, 2013). The response from the global market was, *inter alia,* to lower interest rates to record lows in an attempt to spur economic growth, which saw multiples increase again. Therefore, in order to conduct a proper empirical analysis on multiples, it is equally important to take cognisance of the underlying fundamentals that drive these multiples.

2.4.3   The fundamentals of multiples

The question that inevitably surfaces when dealing with multiples is "At what multiple should an entity's shares trade?" In answering this question, one should have a clear understanding of the three fundamental variables that drive multiples – cash flow generating capacity, growth and risk. The specific measure of each of these key factors will depend on the choice of multiple. Generically, entities with higher growth rates, a greater ability to generate cash flow and lower risk levels, should trade at higher multiples *vis-à-vis* entities with lower growth rates, less ability to generate cash flow and higher risk levels (Damodaran, 2006a). A clear understanding of the underlying fundamental variables that may cause entities in the same sector to have substantially different multiples is important to ensure that the right investment decision is made when comparing multiples across entities.

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Besides a clear understanding of the underlying fundamentals of multiples, it is also important to understand how these fundamentals drive multiples, i.e. how do changes in these fundamentals affect multiples? Many valuation analyses are based on the assumption that there is a linear relationship between multiples and their underlying fundamentals. The Price Earnings Growth (PEG) ratio (P/EPS ratio/expected growth rate in earnings), which is widely used by investment practitioners to evaluate high-growth entities, for example, assumes that there is a linear relationship between the P/EPS ratio and the expected growth rate in earnings. However, there is a common misconception that scaling the P/EPS ratio with expected growth eliminates the effects of expected growth (Damodaran, 2006a). The relationship between growth and value is non-linear and rather complex. In fact, very few, if any, relationships between multiples and their fundamental variables will exhibit linear tendencies (Damodaran, 2006a). These relationships are multi-dimensional in nature. Therefore, when one applies statistical modelling with the aim of offering a simplified representation of a far more complex reality, the estimates of the multiples will not be exact.

However, a careful analysis, via statistical modelling, of the components of each multiple may afford one the opportunity to observe the nature of the relationship between these multiples and their underlying fundamental variables, *ceteris paribus*. Despite the multi-dimensional nature of the relationship between a multiple and its fundamental variables, any multiple will contain one dominant fundamental variable, which predominantly explains a shift in that multiple, i.e. the companion variable (Damodaran, 2006a). The companion variable of any multiple, i.e. the variable that offers the best explanation for differences between entities using that specific multiple, plays an important role in the identification of the correct peer group of entities.

2.4.4 Peer group selection

Multiples-based valuations are typically performed in reference to a peer group of comparable entities. Normally the peer group of comparable entities is selected based on similar industries or business types. However, regardless of the selection process, differences will remain between the entity being valued and the comparable

entity set. A key challenge to a multiples-based valuation is deciding how to control for these differences. Damodaran (2006a) identifies three possible control mechanisms, namely the application of subjective adjustments, the modification of multiples and the use of statistical techniques.

2.4.4.1 Subjective adjustments

In determining whether an entity's share is over- or undervalued, investment practitioners often compare the multiple of the specific share with the mean multiple of the set of comparable entities. If there is a significant difference between the multiple of the specific share and the mean multiple, the investment practitioner makes a subjective judgment as to whether the difference can be attributed to the entity's individual characteristics, such as cash flows, growth or risk. If the investment practitioner fails to attribute the difference to any of these characteristics, he will regard the share as over- or undervalued, depending on whether the share's multiple is higher or lower than the mean multiple of the comparable set of entities. The main criticism of this approach is that investment practitioners may have certain biases towards certain shares, which may cloud their judgments.

2.4.4.2 Modified multiples

An alternative approach to control for differences across entities is to modify multiples by incorporating their companion variables. The P/EPS ratio, for example, can be modified into a PEG ratio, by dividing the P/EPS ratio by its companion variable, i.e. the expected growth rate in earnings. The assumption, then, is that entities are comparable for all the other characteristics, such as cash flow and risk, except for the variable that is controlled for. The other important assumption is that there is a linear relationship between the multiple and its fundamentals, which, as mentioned in Section 2.4.3, is seldom the case.

2.4.4.3 Statistical techniques

Regression analysis affords one the opportunity to measure the strength of the linear or non-linear relationship between the multiple and various independent variables. Contrary to the modified multiples approach, multiple regression analysis allows for the control of more than just one independent variable. The two options that may be followed are market and sector regressions.

In the case of market regression, comparable entities are not selected from the same industry as the entity whose share is being valued, but rather selected on the basis of similar cash flow, growth and risk profiles.

An important consideration when applying sector regression analysis is the definition of the sector. A sector that is too narrowly defined will undermine the validity of regression analysis since this will result in sample sizes that are too small. Although a broader definition may eliminate these limitations, it may lead to more significant differences among entities. Fortunately, these differences can be addressed by a careful consideration of peer group selection methods.

Note that most of these guidelines require the data in a certain format. Optimal peer group selection, for example, requires the creation of peer groups based on industry classification or certain valuation fundamentals, neither of which are readily available from the original data set. Consequently, functions were coded in the *R-package* to accommodate such analysis.

The issues highlighted in Section 2.4 serve as a guide and a sanity check for the construction of unbiased multiples. It is imperative to take cognisance of these potential pitfalls and to adopt a standard approach to mitigate the risk associated with a biased outcome.

2.5   STANDARDISED APPROACH TO MULTIPLES

The traditional multiples-based valuation approach comprises the following four steps (Damodaran, 2009; Schreiner, 2007):

- The first step requires the selection of a set of comparable entities, known as the peer group;

- The second step is to identify the two value relevant measures; namely the MPV and a matching value driver;

- In step three a peer group multiple is estimated based on the entities comprising the peer group selected in step one; and

- Finally, the peer group multiple estimated in step three is multiplied by a value driver of the target entity to determine the value of the target entity's equity.

These steps are implicit in both Damodaran's and Schreiner's methodology. However, Damodaran's and Schreiner's approaches differ in the sequence of steps one and two. While Damodaran argues for the selection of a peer group prior to considering the MPV and value drivers, Schreiner suggests an inverse sequence. Damodaran also suggests the inclusion of an additional step, which requires adjustments to the modelled valuations. For the purpose of this study, the sequence is followed as set out in the paragraph above, while the additional adjustments, as suggested by Damodaran, are regarded as ex-model adjustments and, therefore, excluded from the study.

The potential list of multiples that could be constructed in this manner is long and diverse, and, if unstructured, may hinder a careful analysis. However, the ordering of various multiples in a matrix form may accommodate a structured analysis of the characteristics of any type of multiple. Consequently, a framework of multiples is presented in Table 2.1, based on MPVs and value driver categories, in accordance with the most popular categorisation of multiples.

Table 2.1: Framework of multiples

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

P - Market Price

MVIC - Market Value of Invested Capital

GP - Gross Profit

EBITDA - Earnings Before Interest, Tax, Depreciation and Amortisation

EBIT - Earnings Before Interest and Tax

PAT - Profit After Tax

PBT - Profit Before Tax

HE - Headline Earnings

TA - Total Assets

IC - Invested Capital

BVE - Book Value of Equity

R - Revenue

OD - Ordinary Dividends

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

Source: PwC (2012), Minjina (2008), Damodaran (2006a), Liu *et al.* (2002b),

Alford (1992)

Note: There are value drivers that can reside in more than one value driver category. Ordinary Dividends (OD), for example, can be regarded as a cash flow-based value driver or a dividend-based value driver.[7]

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[7] The assumption here is that script dividends constitute an insubstantial portion of OD.

Figure 2.2 illustrates the most popular multiples that are used by investment practitioners in Southern Africa. As is evident from Figure 2.2, the P/EPS ratio remains the most popular multiple, followed closely by the MVIC/EBITDA and MVIC/EBIT multiples (EBIT refers to Earnings Before Interest and Tax). The popularity and valuation performance of these multiples may vary across markets. While the P/EPS ratio is equally popular in the USA market, for example, the Price/BVE ratio is preferred in Japan (Bildersee, Cheh & Lee, 1990).[8] All the multiples included in Figure 2.2 were incorporated in this study (see Table 2.1). As is evident from Table 2.1, multiples are distinguished based on two value relevant measures, namely MPV and a choice of value driver. However, prior to the identification of the two value relevant measures, a peer group must be selected.
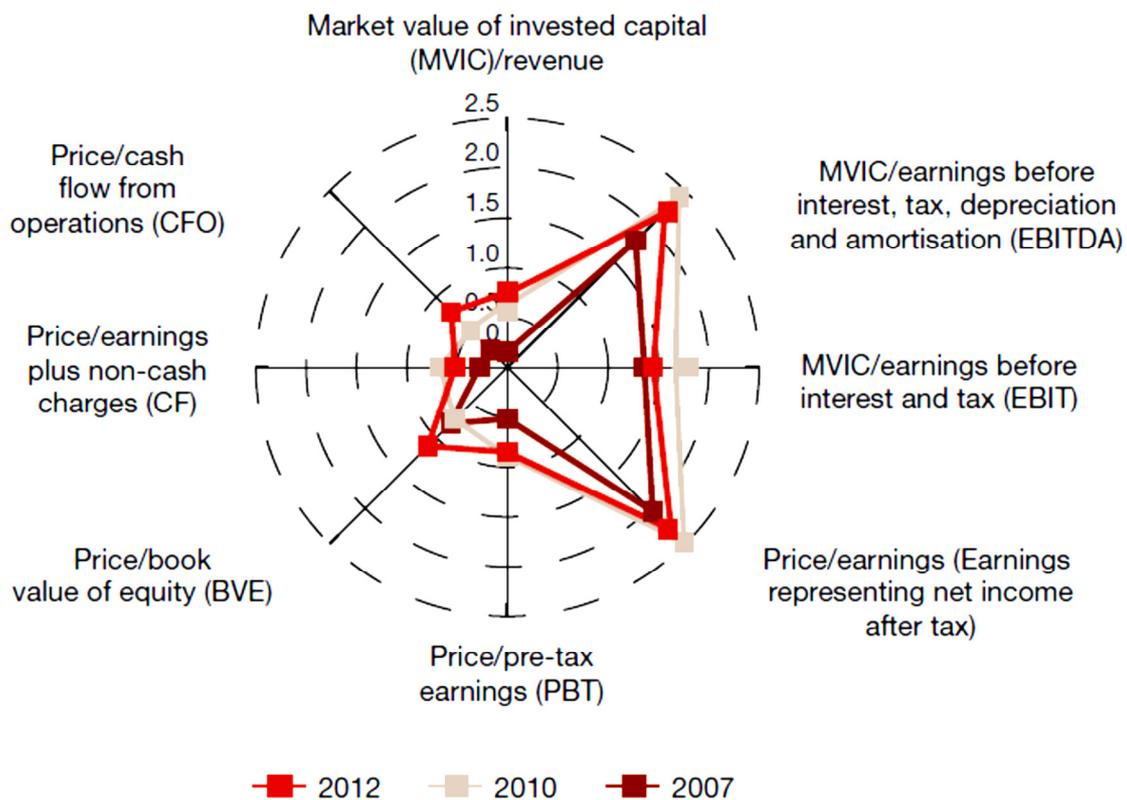
Figure 2.2: Valuation multiples used

Source: PwC (2012)

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[8] There is a growing body of evidence suggesting that, as global markets become more integrated, cross-border multiples may converge (Tam & Tam, 2012). Although global stock market integration is a popular macroeconomic research hypothesis in economic growth empirics, the focus in this dissertation is on the proper construction of multiples in the South African market. Therefore, a detailed analysis of global stock market integration is not elaborated on here.

2.5.1   Peer group selection

The first step in the traditional multiples-based valuation approach requires the identification of an appropriate benchmark multiple, which is based on the selection of a set of comparable entities or a selection of comparable transactions (Stowell, 2010). The comparable entities method rests on the assumption that entities with the same industry classification have similar financial and operational characteristics relating to key fundamental variables such as profitability, growth and risk. The comparable transactions method, which is normally used for valuing merger and acquisition deals, selects historical corporate transactions in the same industry or country as a benchmark (Pratt, 2005). However, as a result of data limitations, the comparable transactions method is less appropriate for statistical analysis. Consequently, this study will focus on the comparable entities method.

The importance of the selection of comparable entities is highlighted in various studies, which also indicate the different areas of application thereof. Despite its obvious application when employing multiples, the selection of comparable entities is also prominent in DCF analysis, for example, where it is used to estimate an entity's cost of capital (Fuller & Kerr, 1981). Various researchers also advocate the importance of comparable entities when investigating the contagion effect, i.e. where actions that affect the value of one entity in a specific industry impact on the value of other entities in the same industry (Bhojraj & Lee, 2002; Eberhart, 2001; Fenn & Cole, 1994; Lang & Stulz, 1992).

Despite the wide application thereof in practice, very little theory is available on how and why certain comparable entities should be selected in certain circumstances. However, there are two schools of thought in this regard (Bhojraj & Lee, 2002). The first school of thought defines comparable entities simply as entities in similar industries. The second school of thought argues that a comparable entity set should be compiled based on similar valuation fundamentals.

2.5.1.1 Similar industries

The implicit assumption when compiling a benchmark multiple based on entities with the same industry classification is that these entities share similar risk, growth and cash flow profiles (Damodaran, 2006a). However, this may prove problematic when there are too few entities in a certain narrowly defined industry, a problem researchers often encounter when using 4-digit codes from the USA Compustat database, for example.[9] To this end, homogeneity is sacrificed to ensure a sufficiently large comparable set by selecting comparable entities based on a broader industry definition, such as a 3-digit industry classification. Similarly, in the South African context, the SUB industry classification from the McGregor BFA database often results in too few comparable entities, in which case the SEC industry classification is used as a broader industry classification.

Industry classification is crucial in the identification of an appropriate peer group of entities. Empirical evidence should guide preferences in this regard and one would be inclined to argue that a narrower industry classification will result in a greater degree of valuation accuracy. This, in turn, raises further questions, such as whether the selection of a peer group based on industry classification alone is sufficient, or whether additional adjustments are required; and what the ideal size of a peer group should be.

Since different industries display different operational and financial characteristics, one would be inclined to expect different multiples to be best suited to different industries (Schreiner, 2007). The primary aim of the industry analysis that is conducted in Chapter 8 is to determine which multiples may be more appropriate – in other words, present a more accurate equity valuation – for which industries. Although, in practice, investment practitioners may place greater weight on certain multiples for certain industries, a detailed theoretical framework indicating which

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[9]   The 4-digit code classification system, which is used internationally, assigns a 4-digit code to each company. The first digit specifies the industry (widest classification), the second digit specifies the supersector, the third digit specifies the sector and the fourth digit specifies the subsector (narrowest classification). The McGregor BFA classification system, which is used in this dissertation, is similar to international classification systems.

multiples are most appropriate for specific industries is not readily available in South Africa.

2.5.1.2 Similar valuation fundamentals

The premise of the valuation fundamentalists is that a comparable entity set consists of entities with similar financial and operational characteristics, i.e. risk, growth potential and cash flows, to the target entity (International Private Equity and Venture Capital Guidelines, 2012; Ivashkovskaya & Kuznetsov, 2007; Damodaran, 2006b). For example, in order to compile a comparable entity set, the target entity's Total Assets (TA), expected Revenue growth (Rg) and Return on Equity (RoE) may be used as a benchmark to identify other entities with similar characteristics. Most existing research builds on the comparable entity principle work of Alford (1992), who found that peer group selection based on similar historical growth within an industry improves the valuation performance of multiples.

It is envisaged that the research results obtained from Chapters 4 and 5 will provide empirical guidance on the basis on which peer group selection should be performed in the South African market. Once this has been accomplished, the focus of the study will turn to the identification of the two value relevant measures, namely MPV and the choice of value driver.

2.5.2 Identifying two value relevant measures

Accounting information is regarded as value relevant if it carries information content that affects market variables (Schreiner, 2007). An entity's earnings, for example, will be value relevant if it has the ability to affect the market price of the entity's shares. So, too, will multiples such as the P/GP ratio (GP refers to Gross Profit), whose construction is based on accounting information. Each of the 16 multiples contained in Table 2.1 is therefore value relevant, since their construction is based on accounting information that was extracted from the entities' financial statements.

2.5.2.1 Market Price Variables (MPVs)

The choice of MPV depends on whether the multiples are equity- or entity-based, an issue that is addressed in Chapter 6. Equity-based multiples are based on the market price of a share or the Market Capitalisation (MCap) of an entity. Entity-based multiples, on the other hand, are based on MVIC, i.e. MCap plus preference share capital plus interest-bearing debt.[10] Equity-based multiples would appear to offer a simpler approach, since market capitalisation does not require a further adjustment for debt, as is the case with entity-based multiples. However, from a theoretical point of view, one would be inclined to argue that entity-based multiples should outperform equity-based multiples due to the fact that they are less affected by different capital structures among comparable entities (Foushee, Koller & Mehta, 2012; Suozzo, Cooper, Sutherland & Deng, 2001).

In practice, investment practitioners may have preferences for equity- or entity-based multiples. For example, while portfolio managers may prefer equity-based multiples, investment bankers may have a preference for entity-based multiples (Schreiner, 2007). However, regardless of these preferences, valuation logic dictates that investment practitioners should take cognisance of the matching principle when constructing multiples, i.e. the choice of value driver should match the choice of MPV (Damodaran, 2006a; Pereiro, 2002). This will ensure a proper distinction between equity- and entity-based multiples. Therefore, when using equity-based multiples, only equity holders' claims should be considered, while entity-based multiples (i.e. where MVIC is used as an MPV) constitute claims of all fund providers of the entity. In the case of equity-based multiples, the denominator could be one of many items from the statement of comprehensive income, the statement of financial position and the statement of cash flows.

Valuation theory suggests that entity-based multiples offer several benefits over equity-based multiples. Firstly, entity-based multiples are more comprehensive than

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[10] There are various definitions of entity value, which may include/exclude long/short-term debt and include/exclude cash and cash equivalents. The definition applied throughout the dissertation is generally referred to as MVIC.

equity-based multiples since they value the business as a whole, whereas equity-based multiples focus solely on equity value. Secondly, entity-based multiples are less affected by capital structure differences among entities (Stumpp, 2000). Thirdly, the value drivers that are generally associated with entity-based multiples, such as EBITDA, are less susceptible to accounting differences caused by differences in entities' tax structures or depreciation policies, for example. Consequently, entity-based multiples are more comparable between entities than equity-based multiples. Therefore, based on valuation theory, one may be inclined to expect a superior valuation performance from entity-based multiples relative to their equity-based equivalents.

The valuation performance of equity- and entity-based multiples may be hindered by two caveats. The equity-based caveat is gleaned from conventional capital structure theory, which states that the level of gearing affects the cost of capital and therefore affects valuations. As the level of gearing increases, the costs of financial distress will also eventually increase, which, in turn, will increase the financial risk and therefore the cost of equity. The optimal level of gearing is where the Weighted Average Cost of Capital (WACC) is at its minimum, i.e. where the bowl-shaped WACC curve bottoms out.

On the contrary, the Modigliani and Miller (1958) theory assumes that all investors are rational and operate in a tax-less world, with zero transaction costs, zero costs of financial distress and in the absence of asymmetric information and agency problems. Not surprisingly, capital structure in the Modigliani and Miller environment becomes value-irrelevant, i.e. capital structure has no effect on WACC or equity and entity value. However, if the Modigliani and Miller theory holds, different capital structures between entities could erroneously affect equity-based multiples (Schreiner & Spremann, 2007). This would occur if equity-based multiples were not defined consistently. Executives may also be tempted to substitute debt with equity in order to orchestrate higher equity-based multiples (Chadda, McNish & Rehm, 2004).

In reality, investors do not always behave rationally and they do pay taxes and incur transaction costs. Investors may also encounter debt restructuring, insider trading and a conflict of interest with management. In short, capital structure is value-

relevant, i.e. capital structure decisions affect the cost of equity and, therefore, affect equity and entity value. This fact was later conceded by Modigliani and Miller (1963), after they had indicated that the tax shield of debt does, in fact, affect shareholder value. Therefore, in reality, capital structure decisions also have a bearing on equity- and entity-based multiples.

The problem pertaining to agency costs, especially in larger entities, stems from the separation of ownership and control. In general, key decision making agents of an entity will not carry a substantial portion of the impact of their decisions on shareholder wealth (Fama & Jensen, 1983). This may be a particular point of contention when an entity possesses a sizeable war chest. Whereas shareholders may be in favour of higher debt levels to prevent their agents from overcommitting an entity's free cash flows to less profitable opportunities, this, in turn, may severely hamstring the agents' flexibility to invest in lucrative investment opportunities should they arise. This will have a direct bearing on entity and equity value. So, too, will the asymmetric information dissemination between an entity's agents and market participants regarding the value of the entity and its equity.

More pragmatic capital structure decision theories have been documented since Modigliani and Miller's original work. These include trade-off-, pecking order-, signalling- and market timing theories, all of which concede that capital structure is value relevant (Baker & Wurgler, 2002; Myers, 1984; Myers & Majluf, 1984; Kraus & Litzenberger, 1973).

An equally rich volume of empirical literature exists on the value relevance of ownership structures. Although the original research conducted in this field can be traced to earlier work by Berle and Means (1932), Jensen and Meckling (1976) were the first to show how insider and outsider equity holdings influence the value of an entity. These findings were refined by McConnell and Servaes (1990), who found a strong positive relationship between insider equity ownership and entity value at equity stakes of less than 5%. Their results also indicated that there is a strong positive relationship between institutional investor equity ownership and entity value,

while no significant relationship exists between equity block ownership and entity value.[11]

The entity-based caveat revolves around the market values of preference shares and debt. The MPV (MCap) that is used to create equity-based multiples is readily available in the market. However, since the market values of preference shares and debt are not readily available in the market, no equivalent MPV (MVIC) exists in the market for the creation of entity-based multiples. As an alternative, MVIC is calculated by adding the book values of preference share capital and debt to MCap. Although these book values may be reasonable proxies for their respective market values, they could generate considerable noise if the circumstances surrounding their issuance have changed considerably. Consider, for example, the impact of a significant change in the interest rate or default risk of debt since its issuance (Koller, Goedhart & Wessels, 2005). Different entities may also have vastly different debt structures, which severely complicate the calculation of an appropriate debt figure, i.e. the nature of entities' debt may be very different. For example, entities may have more or less long-term, compared to short-term, debt or more or less convertible, compared to non-convertible, debt. Entities may also employ different accounting methods to pension liabilities or share options, for example. Similarly, the market value of preference share capital, which may also not be publicly available, could cause considerable noise.

Therefore, an equity-based MPV seems to offer a simpler alternative compared to an entity-based MPV since there is only one share price at any point in time. However, investment practitioners may need to exercise due care when selecting market price data from a database. There are various reasons for this. Firstly, entities may issue various classes of shares, which will trade at different prices. The market capitalisation will include the value of all the different classes of shares in issue, whereas the market price will merely reflect that of the specific shares being considered, which, for the purpose of this study, would be ordinary shares. Secondly,

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[11] The related literature presents further extensions on the relationship between ownership structure and entity value, which, among others, highlights the role of corporate governance and legal institutions in the protection of minority rights in particular. However, since the theoretical focus in this dissertation is on the proper construction of multiples, these issues are not elaborated on here.

it may be necessary to consider the equity values ex-cash. The risk and return characteristics of cash holdings would probably differ significantly from that of operating assets, which may warrant the use of an equity value net of cash holdings, especially when entities hold large cash balances. Lastly, secondary claims on equity posed by equity options and convertible securities, for example, may require an equity-value adjustment to obtain the total market value of equity, including the value of these options.

2.5.2.2 Value drivers

The valuation performance of value drivers and the value driver categories in which they reside are investigated in Chapter 7. Value drivers are gleaned from different sections of the statement of comprehensive income, the statement of financial position and the cash flow statement. The value driver categories employed in this study reflect the figures from the financial statements that are used most frequently in international literature, namely earnings, assets, revenue, dividends and cash flows.

Different circumstances may warrant the use of different value drivers. For example, earnings-based multiples will be nonsensical when an entity is making losses, in which case revenue-based multiples may be a workable alternative. Therefore, a firm grasp of the nature and limitations of the respective value drivers is key to the construction of appropriate multiples.

a.   Earnings-based value drivers

The primary criticism of earnings-based value drivers is that they are based on accounting measures which may be manipulated. Wetherilt and Weeken (2002) even suggested that the dividend yield model is preferable to the P/EPS ratio, as a result of accounting malpractices. These malpractices have raised doubts concerning the quality of earnings, which is an important consideration when employing earnings-based multiples.

Although entities' share prices generally respond well when actual earnings results exceed consensus forecasts, careful consideration should be given to the quality of these earnings. If the earnings results do not emanate from earnings growth and/or cost reductions, the quality thereof may be dubious. For example, if Entity A and Entity B report earnings in excess of consensus forecasts, they may both present investment opportunities. However, of equal importance is the quality of these earnings, i.e. the manner in which they were achieved. Entity A may have sold its assets, while Entity B may have achieved their results by reducing costs. While Entity A will not be able to generate earnings continually by selling their assets, Entity B will continually benefit from their cost reductions, i.e. Entity A manufactured a one-off earnings boost, while Entity B implemented a perpetual benefit. Clearly, the quality of Entity B's earnings is higher than that of Entity A.

Uncontrollable macro-economic factors, such as exchange rates and inflation, may also obscure the quality of earnings. Consider, for example, a South African entity that has to convert USA dollar earnings into South African rand against a depreciating ZAR/US$ exchange rate. Management has no control over a favourable move in the exchange rate and will therefore not be able to replicate it. Similarly, inflation may present a temporary boost in earnings when inventory is sold at inflated prices.

In the same vein, earnings growth may be generated by an increasingly large debtors' book, which does not constitute cash in the bank. The uncertainty regarding the collectability of these earnings decreases the quality of these earnings. Intuitively, cash earnings constitute the highest quality of earnings.

Even if accounting measures are not manipulated, they still rest on accounting rules and principles, which may be applied differently by different entities (Nel, 2009a). This highlights a second point of criticism. The application of discretion when accounting for expenses such as depreciation and amortisation, for example, may deviate substantially from actual economic value declines as they are based on *ad hoc* estimates, as derived from historical cost, a further shortcoming (Liu *et al.,* 2002b). Since accounting figures are historical by nature, multiples based on these figures are calculated on the assumption that history is bound to repeat itself.

The earnings-based value drivers that are investigated in this study are listed in the first value driver column in Table 2.1. All six of these value drivers emanate from the statement of comprehensive income. Complete definitions of all 16 value drivers are provided in Annexure A.

Gross Profit (GP)

GP is a reflection of an entity's operational efficiency. While Entities A and B, for example, might both be generating the same amount of revenue, they might be realising vastly different amounts of GP. If Entity A is able to generate a higher GP, this may reflect its ability to generate revenue more efficiently compared to Entity B.

Unfortunately, most of the advantages of GP multiples also carry inherent disadvantages. Consider, for example, the location of GP on the statement of comprehensive income. Since GP is located quite high up in the statement of comprehensive income it is less susceptible to manipulation compared to value drivers that are located further down. However, its location so high up in the statement of comprehensive income means that it is also rather removed from the reality of the financial bottom line, which renders it less useful in the market place.

As one would expect, the GP multiple has a strong positive correlation with Rg. However, such growth may be misleading if it is manufactured, for example, by selling goods or services to customers at below cost. Although customers may embrace such a value for money offering, it is not a sustainable business offering and will ultimately culminate in a growing concern issue.

The size of the GP multiple is linked to the gross margin. Therefore, high variable costs will erode profits and will culminate in higher GP multiples.

Earnings Before Interest, Tax, Depreciation and Amortisation (EBITDA)

Per definition, EBITDA excludes interest expenses, taxes, depreciation and amortisation. Debt repayments or interest payments are ignored, since they are regarded as a function of management's choice of financing. Taxes are excluded since they can vary greatly between different entities, depending on assessed losses and an external growth drive, which may distort profitability. Adding back depreciation and amortisation removes the distortion caused by subjective judgments regarding useful lifespans and various depreciation methods, for example, which may obscure the calculation of depreciation and amortisation.

Aside from the misguided benefit that EBITDA is likely to make most entities appear profitable, why does it remain such a popular value driver among investment practitioners? EBITDA multiples are particularly useful since they eliminate intercompany discrepancies that might be caused by the factors that they isolate. More specifically, they aid the comparison of entities with different capital structures, tax rates and depreciation policies. It is evident why EBITDA multiples became so popular with the spurt of leveraged buy-outs in the 1980s, especially in capital-intensive industries (Stumpp, 2000).

What makes EBITDA particularly useful in a multiples-based valuation analysis is that it is less likely to result in negative multiples compared to Profit Before Tax (PBT) or EBIT, for example. Eliminating entities with negative multiples tends to bias the peer group multiple and, subsequently, the valuation estimate. EBITDA multiples are less prone to such bias since they are calculated prior to the depreciation charge being levied, which is why they became such popular value drivers in the 1980s. This particularly holds true for entities with large infrastructural expenditures, and therefore large depreciation charges, on their statements of comprehensive income (Damodaran, 2006a).

However, there is a spate of cautionaries in the financial literature, heeding investment practitioners against the blind use of EBITDA multiples, warning that they may present a tainted picture of an entity's profitability and financial health. What are these caveats associated with EBITDA?

Firstly, EBITDA ignores debt-related payments. Therefore, an entity may artificially boost its earnings by incurring debt, the service of which will not be accounted for in this value driver. Interest payments represent actual cash outflows. They are real cash outflows from the entity and must be honoured. The going concern assumption, on which any entity rests, depends on the ability of the entity to make interest payments.

Secondly, EBITDA ignores tax payments. Consequently, the value driver will not indicate when an entity is incurring after-tax losses. As with interest charges, tax payments represent real cash outflows from the entity. These cash outflows are non-discretionary, i.e. they must be paid.

Thirdly, continuous capital expenditure, which may be significant, is an important element for most entities. Depreciation and amortisation may be non-cash charges, but they are non-avoidable expenses. Equipment will eventually have to be replaced and funds will have to be put aside for this purpose.

Fourthly, EBITDA ignores the reinvestment needs of the entity, i.e. cash requirements for working capital needs and capital expenditure. What can be more critical for an entity's ability to continue operating as a going concern? Ignoring the cash requirements of daily operations is especially problematic in the case of growth entities, where an increased investment in inventory and accounts receivable acts as the catalyst converter of growth into sales.

Lastly, and most importantly, while EBITDA may be a useful measure of profitability, it is not an appropriate proxy for cash flow. EBITDA creates the illusion of profitability, especially in terms of cash profits, by ignoring major expenses such as depreciation. Using EBITDA as a proxy for cash flows is misleading since there are significant differences between the two. This is a common misconception, i.e. that valuations based on EBITDA multiples represent cash earnings, since they exclude depreciation and amortisation, which are non-cash charges. If investment practitioners wish to employ a cash flow-based value driver they should select one from the cash flow statement.

Earnings Before Interest and Tax (EBIT)

EBIT is a somewhat broader value driver than EBITDA, since it does take into account two non-cash items, namely depreciation and amortisation. EBIT focuses on the entity's ability to generate profits. More precisely, it reflects profits before taking interest payments and income taxes into account. Therefore, as with EBITDA, EBIT's popularity as a value driver stems, in large part, from the fact that it eliminates disparities between entities with different capital structures and tax rates and thereby simplifies cross-company comparisons.

However, these benefits may also be a cause for concern for investment practitioners. Similarly to EBITDA, EBIT does not account for debt and interest repayments and tax payments. Therefore, as with EBITDA, management may artificially boost an entity's earnings and disguise the fact that they are incurring after-tax losses.

Investment practitioners should therefore refrain from using EBIT in isolation, but rather use it as a measure of inter-company profitability. An analysis based on value drivers that measure operational profitability, as reflected by EBIT, may yield very different results compared to an analysis based on value drivers such as PBT, that incorporates interest, and Profit After Tax (PAT), that incorporates interest and tax.

Profit Before and After Tax (PBT and PAT)

PBT is a profitability measure net of all expenses, including interest payments and operating expenses, but before tax payments. As a pre-tax measure of an entity's operating performance, PBT eliminates the potential impact of complicated tax structures that may vary substantially between entities. Since PBT accounts for interest repayments, which EBIT ignores, it also eliminates the risk of artificially boosting the earnings figure without reflecting the accompanying financial risk. Finally, PAT offers the financial bottom line, reflecting an entity's profitability after taking into account all of its expenses, including tax payments.

Headline Earnings (HE)

HE measures an entity's sustainable profits. It ignores any one-time occurrences, such as losses incurred by writing off a loss-making division, since these events may distort the earnings figure. Assuming that these entities are financially sound and that these one-off events are unlikely to reoccur, they are not indicative of the future health of an entity and are therefore not included in this value driver. Although not completely immune to earnings manipulation, HE is regarded by many investment practitioners as a more robust and comparable figure than its earnings-based counterparts. However, a careful analysis of the items excluded from this value driver is probably warranted.

b.   Asset-based value drivers (TA, Invested Capital (IC), BVE)

Asset-based multiples are best suited to entities operating in capital-intensive industries, such as the oil and gas space, where tangible assets are the main value drivers, or in the financial services industry where financial assets are the main value drivers (Frykman & Tolleryd, 2010). However, all three asset-based value drivers included in this study, namely TA, IC and BVE, suffer the same drawback as earnings-based value drivers, i.e. they rest on accounting principles and may be accounted for based on historical costs. Consequently, asset-based value drivers are susceptible to the same criticism as earnings-based value drivers in this respect. Besides the fact that asset-based value drivers are affected by the accounting treatment of items such as depreciation, they may have little relevance for entities with limited tangible assets, such as technology entities (Damodaran, 2002). Asset-based multiples also fail to reflect an entity's ability to generate earnings or cash flows.

c.   Revenue (R)-based value drivers

The major benefit of employing R-based value drivers is that they are far less susceptible to accounting manipulation than earnings- and asset-based value drivers

(Damodaran, 2006a). Earnings- and asset-based value drivers are influenced by accounting decisions regarding depreciation, for example, while revenue is far more difficult to manipulate. Consequently, R-based multiples are easier to compare across different markets and are less prone to bias in the comparison process.

R multiples may be among the crudest multiples available and supporting a potential transaction with such a crude measure is risky. The latter was an unfortunate trend during the dot-com bubble in the late 1990s, which is why investment practitioners should take cognisance of the fact that not all revenue is created equally (Gurley, 2011). Therefore, a careful analysis of the quality of the revenue is required when performing valuations based on R multiples. The following factors should be considered to gauge the quality of R:

Firstly, the revenue of an entity with strong barriers to entry and the ability to sustain its competitive advantage in the foreseeable future, for example, will constitute a higher quality than the revenue of an entity with little or no sustainable competitive advantage. Investors will be positive about the ability of an entity such as the former to generate revenue consistently into the future.

Secondly, investors have a keen interest in the visibility of an entity's future revenue stream. Business models that rely on subscription revenue, especially when low churning rates apply, may take longer to reach scale, but once they do, they will command higher multiples. This can primarily be attributed to the repetitive nature of the revenue stream *vis-a-vis* one-off revenue streams in consulting business environments, for example. In a similar vein, the revenue stream of non-subscription based businesses will command more pricing power when high customer switching costs apply.

Thirdly, does the Rg feed into the financial bottom line? It is equally important to convert Rg into increased profitability. An incremental operating margin is an indication that Rg is outpacing cost increments, which is sure to command higher multiples.

Fourthly, an analysis of the customer base is required. A more diversified customer base will command a higher multiple than a more concentrated one. A concentrated customer base is indicative of market power, which may severely hamper an entity's pricing strategy, and therefore the ability to enhance the financial top line.

Fifthly, the level of partner dependencies must be considered. If an entity is highly dependent on a partner entity in some way to generate revenue, this will be reflected in lower multiples. The investor logic is that such entities are exposed to risk factors beyond management's control.

Sixthly, the nature of the demand for an entity's products and/or services warrants consideration. An entity that lures its customers with heavy advertising budgets will trade at lower multiples compared to entities that generate revenue via word of mouth. Investors will prefer business models based on organic growth to those based on the buying/renting of customers.

Although it may be a useful multiple when valuing loss-making entities, e.g. start-ups and distressed entities, revenue is the first entry in the statement of comprehensive income and therefore does not take into account any expenses, which may also disguise unprofitable businesses. However, the risk of creating bias by eliminating entities with negative multiples for the estimation of peer group multiples, as is the case with earnings, for example, does not exist for revenue.

R multiples are also less volatile than earnings multiples. This stems from earnings-based value drivers being located further down in the statement of comprehensive income, thereby involving a greater number of variables to which earnings based-value drivers are more sensitive. Consequently, the P/EPS multiple, for example, will vary considerably more than the P/R multiple.

The important consideration is that, regardless of the high Rg that an entity generates, it may still be incurring losses. Valuations may be misleading if they are performed without controlling for differences in costs and profit margins between entities. In the long run, an entity has to generate earnings and cash flows to

continue existing as a going concern. Unfortunately, R multiples offer little comfort in this regard.

d.   Dividend-based value drivers (OD)

OD seems a logical choice for a value driver since many investors invest in order to receive dividends. It is also a good value driver for comparing inter-company cash-based investment returns, assuming that OD contains an insubstantial portion of script dividends. However, dividend pay-outs are dependent on an entity's dividend policy, which may be altered at any time. Young start-up entities with high growth potential, for example, may be inclined to retain earnings to fund internal growth. OD multiples, however, largely ignore the platform for growth that is offered by retained earnings. An entity may also refrain from paying a dividend, which may render the use of OD as a value driver nonsensical. Apart from the uncertainty surrounding the sustainability of dividends, there are also jurisdictional differences in tax treatments that may impact on investor returns.

e.   Cash flow-based value drivers

Cash flow-based value drivers are less susceptible to manipulation than their accrual-based counterparts. Less so, but not immune, according to Mulford and Comiskey (2002). This sentiment was shared by Charles Niemeier, then chief accountant of the Securities and Exchange Commission's (SEC_1's) enforcement division, that, after Enron's demise, highlighted entities' tendency to abuse accounting standards when defining cash flow (SEC_1, 2002). Cash flow is a more accurate reflection of an entity's actual performance than earnings. While earnings are based on accounting principles and estimates, cash flow reflects actual cash received and paid during a given period (Fink, 2002).

On the other hand, even cash flow-based value drivers are prone to interpretation, as reporting practices may vary between entities in terms of operational cash flows, for example. Does cash flow generated from the securitisation of receivables, for

example, form part of cash flow from operations or should it be included under financing activities? Despite these uncertainties, cash flow measures such as FCFF take changes in capital expenditure and working capital, for example, into account, while earnings-based multiples tend to ignore them.

Cash generated by Operations (CgbO)

CgbO is the most broadly defined value driver in the cash flow-based value driver category. Although CgbO reflects cash flows after accounting for working capital, it is a pre-tax measure of an entity's operational cash flows and ignores financing charges. Its pre-tax nature eliminates the potential impact of complicated tax structures, which may vary substantially between entities. However, it may also disguise after-tax losses. Since it ignores finance charges, CgbO may, as in the case of EBITDA and EBIT, be boosted without taking the accompanying financial risk into account.

Compared to its earnings-based counterparts, CgbO largely mitigates the risk of manipulation and accounting rule distortion by management, which explains why investment practitioners often consider this value driver in conjunction with an earnings-based equivalent, such as PBT. A substantial disparity between these two value drivers may cast doubt over the quality of earnings and is likely to highlight liquidity issues.

Net Cash Inflow from Operating Activities and Net Cash Inflow from Investment Activities (NCIfOA and NCIfIA)

NCIfOA and NCIfIA are post-tax measures that account for financing charges and dividends. Since both measures account for interest payments, they cannot be artificially boosted, i.e. without accounting for the accompanying financial risk. In addition, NCIfIA also takes into account net capital expenditure, which is necessary to maintain an entity's operational capacity. Therefore, it reflects an entity's cash profitability after accounting for all the major cash expenses, including the

reinvestment needs of the entity. However, the distinction between operating, investing and financing activities may complicate the calculation of NCIfOA and NCIfIA. The accounting treatment of the securitisation of receivables, mentioned earlier in Section 2.5.2.2.e, serves as an example.

In the case of NCIfIA, the costs and benefits of capital expenditure may be separated by a substantial time delay. While the immediate capital expenditure reduces NCIfIA instantly, effectively reducing the value of the equity/entity, the benefits may only be realised over an extended time period. Unfortunately, this may present an agency problem, i.e. management may be tempted to orchestrate an artificially higher NCIfIA figure in the short term at the expense of new investment opportunities.

Free Cash Flow to the Firm and Free Cash Flow to Equity (FCFF and FCFE)

Free cash flows are normally calculated for DCF-based modelling purposes. Unlike NCIfOA and NCIfIA, FCFF and FCFE are not affected by the entity's capital structure, since non-operational items such as net interest and net dividends are added back. Therefore, FCFF and FCFE can be regarded as a full entity dividends, i.e. the dividend that an all-equity entity can pay out if it had a dividend pay-out ratio of one (Schreiner, 2007).

FCFF and FCFE carry the same caveat as NCIfIA in that immediate capital expenditure reduces FCFF and FCFE instantly, effectively reducing the value of the equity/entity, while the accompanying benefits may only materialise beyond the horizon period. As in the case of NCIfIA, this may present an agency problem.

f.   **Forward multiples**

The value driver discussion thus far has focused primarily on value drivers that are based on historical figures, commonly referred to as trailing multiples. However, valuation exercises are, by definition, forward-looking. An asset's current value is usually a reflection of future benefits that will be derived from the use of the asset.

According to International Accounting Standard (IAS) 16 (Pretorius, Venter, Von Well & Wingard, 2010a), an asset should be recognised when it is possible that future benefits associated with it will flow to the entity and the cost of the item can be measured reliably. If one applies similar logic within the context of valuations, one would expect that forward multiples, which are based on forecast value drivers and should therefore reflect future accruals/flows, would exhibit a higher degree of valuation accuracy than trailing multiples.

Alternatively then, the value driver can be a forecast figure, such as forecast earnings or revenue, in which case the multiple is referred to as a forward multiple. However, data availability presents a challenge when researching forward multiples. Although databases such as McGregor BFA, I-Net Bridge and Thomson Reuters contain investment practitioners' forecasts in this regard, the data is usually limited, i.e. only available for EPS, Dividend Per Share (DPS) and Earnings Yield (EY), or only available for a limited number of years. Thomson Reuters, for example, only lists consensus investment practitioner forecasts from 2008 onwards for R, EBITDA, EBIT, Earnings Before Tax (EBT) and Earnings (E). Consequently, forward multiples are not included in this study, but they are a topic for future research.

2.5.3   Estimating the peer group multiple

Subsequent to the selection of the entities for inclusion in a peer group, peer group multiples must be estimated. Although several statistical methods exist to aid this calculation, there appears to be a lack of consensus in academic research regarding the use of the median, arithmetic mean or the harmonic mean as averaging procedures (Dittman & Maug, 2008). Pratt and Grabowski (2008) argue that the arithmetic mean is inappropriate since it is excessively affected by outliers. In this study, the harmonic mean is preferred to estimate industry multiples, primarily because it avoids the upward bias of the arithmetic mean.[12] Baker and Ruback (1999) suggest that, empirically, the harmonic mean is closer to the minimum variance estimates deduced from Monte Carlo simulations than the simple mean,

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[12]   The harmonic mean is the reciprocal of the arithmetic mean of the reciprocals. Mathematically it equates to the following: $\dfrac{n}{\sum_{i=1}^{n}\left(\frac{1}{x_i}\right)}$

median or value-weighted mean. In addition, Liu *et al.* (2002b) regard the harmonic mean as a viable and unbiased estimator. Beatty, Riffe and Thompson (1999) and Bhojraj and Lee (2002) also prefer the use of the harmonic mean.

2.5.4　Calculating the target entity's equity or entity value

This is the final step in the valuation of an entity or its equity. This step is explained in detail in Chapter 3 and is consequently only described briefly here. The peer group multiple is multiplied by a target entity's value driver, such as EBIT or R, for example, to value the target entity or its equity (Goedhart *et al.,* 2005). This is in line with multiples-based valuation theory, which holds that the Actual equity value (V_{it}^{e}) of an entity (i) at a given point in time (t) is equal to the product of an Actual equity-based multiple (λ_{t}^{e}) and a specific Actual value driver (α_{it}) at that specific point in time, so that

$$V_{it}^{e} = \lambda_{t}^{e} \cdot \alpha_{it} \qquad\qquad (2.8)$$

Note that Equation (2.8) refers to equity-based multiples in particular. The valuation of equity by means of entity-based multiples will require the use of similar entity-based equations. Equation (2.8) is adjusted by replacing the equity-based multiple (λ_{t}^{e}) with an entity-based multiple (λ_{t}^{n}) and Debt (d) is deducted from the entity value ($\lambda_{t}^{n} \cdot \alpha_{it}$) to obtain the equity value:

$$V_{it}^{e} = \lambda_{t}^{n} \cdot \alpha_{it} - d \qquad\qquad (2.9)$$

The first three steps in the standard approach to the construction of multiples again require the data in a certain format. Optimal MPVs, for example, require the creation of equity- and entity-based multiples, neither of which were readily available from the original data set. Consequently, functions were coded in the *R-package* to accommodate such analysis.

The MPVs and value drivers discussed in Sections 2.5.2.1 and 2.5.2.2 above are generally used in single factor multiples models. However, an interesting question that has surfaced in the literature over the past five years relates to the use of a combination of individual multiples, which, it is suggested, may harness a value contribution in terms of increased valuation accuracy. This has resulted in a new avenue of research into the valuation accuracy and the potential valuation performance enhancement that may be contained in composite multiples models.

2.6   COMPOSITE MULTIPLES MODELS

Valuation theory suggests that, when applying different valuation methods to the same entity, each method will yield a different answer. The question as to which method is superior is a subject of much debate within academia and practice (Nel 2010; 2009b; Kamstra, 2003). An important consideration in this regard is that no single valuation method has a *carte blanche* application across the board, i.e. different valuation methods are best suited to different circumstances (Pratt & Niculita, 2007).

Consequently, not only do various valuation methods find their way into investment practitioners' reports, but so too do various multiples. In the case of multiples, in particular, one would expect to find an array of different multiples, all applicable in slightly different circumstances. This approach seems to suggest that single factor multiples carry incremental information. Therefore, one would be inclined to argue that a combination of value estimates into an aggregate estimate may provide a superior value estimate. This is the premise for the research hypothesis. A composite value estimate ensures that the incremental information is encapsulated in a superior value estimate and that biases and errors in individual estimates are averaged out (Yee, 2004).

But how should this be accomplished? Despite the simplicity of the potential value contribution that a composite value estimate may offer, the literature offers little

guidance to practitioners in this regard. Based on the Delaware Block Method[13], Bayesian decision theory[14] and forecasting, Yee (2008) suggests adhering to the following guidelines when attempting to combine value estimates:

- Value should be estimated as a linear weighted average of all available value estimates.

- Incorporate as many *bona fide* value estimates as possible.

- Assign a greater weight to those value estimates that you deem more precise.

- The application of an equal weight to all available value estimates usually works just as well as more sophisticated weighting procedures.

- Statistical back testing may prove helpful when determining optimal weights.

The theoretical background presented in Chapter 2 highlighted the complexities surrounding the proper construction of multiples. Based on these complexities, the need was identified to investigate the six research questions, as illustrated in Figure 1.3. However, prior to investigating these six research questions in further detail, it is necessary to first consider an appropriate research methodology.

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[13] The Delaware Block Method refers to an equally weighted value composite consisting of three value factors, namely the market price, the net asset value and the five-year trailing earnings average.

[14] Bayesian decision theory holds that all value relevant factors should be included in a value composite and that more weight should be given to the more credible estimates.

CHAPTER 3

RESEARCH METHODOLOGY AND DATA SELECTION AND ANALYSIS

3.1 INTRODUCTION

Prior to specifying and estimating the composite multiples models, a careful analysis of the data set is required in order to establish the properties of the data, i.e. its asymmetric nature, the presence of outliers, data distribution, collinear relationships, etc. The latter will be crucial for the development of a well-structured and detailed analysis of the variables involved. The empirical investigation will be divided into two broad categories, namely a cross-sectional analysis and an industry analysis. For the purpose of answering the first four research questions, the traditional single factor multiples model is tested by means of a cross-sectional analysis, which is partly based on the methodology followed by Alford (1992) and Liu, Nissim and Thomas (2002a).

However, since the first two research questions focus on the appropriate selection method of the comparable entity set *per se,* modification of the McGregor BFA industry classification is required. For the purpose of answering research question one the McGregor BFA industry classification will be refined consecutively, from the IND level through to the SUB level. For the purpose of answering research question two, none of the McGregor BFA industry classifications is applicable. Peer group selection, in this case, will be based on three valuation fundamentals or a combination thereof. Research questions three and four are also addressed by means of a cross-sectional analysis.

Research questions five and six are approached by means of an industry analysis, for which the basis of peer group selection will depend on the outcome of research questions one and two. Research question five is addressed by testing the valuation accuracy of industry-specific multiples, while research question six entails a comparison between composite and single factor multiples models. The

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methodology used for the industry analysis is partly based on the methodology followed by Schreiner (2007). The research methodology which will be employed to answer the first five research questions will be based on single factor multiples, while the methodology applied to answer research question six will include composite multiples.

3.2   DATA SELECTION AND ANALYSIS

The study constitutes a quantitative empirical investigation into the valuation performance of various multiples in the equity valuation of entities that were listed on the JSE over the period 2001 to 2010. To this end, the data is obtained from the McGregor BFA database, one of the leading data houses in South Africa (PwC, 2012). The McGregor BFA database contains a standardised data set, which aids comparison.

The main hurdle encountered with the McGregor BFA database pertained to data entries from foreign entities, specifically the translation of foreign currency-based financial statements, which initially hampered comparison. The translation of foreign currency-based financial statements, specifically the statement of comprehensive income and the cash flow statement, was approached incorrectly in the McGregor BFA database, according to the closing rate method, i.e. based on exchange rates as at the date of the statement of financial position.

IAS 21 states that income and expenses in the statement of comprehensive income should be translated based on the exchange rates on the dates of the transactions concerned (Pretorius, Venter, Von Well & Wingard, 2010b). However, where this is impractical, which is typically the case, an average exchange rate can be applied, provided that the specific exchange rate is not significantly volatile. The same rule applies for the cash flow statement. Where applicable, the figures employed in the study were subsequently corrected before conducting the analyses.

The following variables were extracted from the McGregor BFA database: Market Capitalisation (MCap), Shares in issue, Gross Profit (GP), Earnings Before Interest,

Tax, Depreciation and Amortisation (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), Revenue (R), Cash generated by Operations (CgbO), Increase/decrease in working capital, Net Cash Inflow from Operating Activities (NCIfOA), Net Cash Inflow from Investment Activities (NCIfIA), Ordinary Dividends (OD), Taxation paid, Fixed assets acquired, Net interest paid/received, Secondary tax on entities, Capital profits/losses on financial assets, Normal taxation included in extraordinary items, Total profit of an extraordinary nature, Industry (IND), Supersector (SUP), Sector (SEC), Subsector (SUB), Entity name (CPY) and Ticker symbol (TIC).

Entity year observations for these variables for the period 2001 to 2010 were extracted from the McGregor BFA database. The entities were selected based on three criteria: 1) All multiples are positive; i.e. multiples with negative values were discarded, 2) The entities have at least three years of positive entity year multiples, and 3) Each industry classification category has at least four observations that meet criteria 1) and 2) above. Although many entities' industry classifications have changed over the period 2001 to 2010, for the purposes of this study, entities were allocated to the industries where they resided as at 31 December 2010.

The first condition eliminates unrealistic multiples that cannot be used. Note that discarding negative multiples does not infer that entities, or their equity, with negative value drivers have no value. However, scaling prices with negative value drivers will produce negative company values, which is impractical. In fact, these entities, or their equity, should rather be valued by deflating price with another (positive) value driver or by applying an alternative valuation approach. For a more detailed discussion in this respect, see Collins, Pincus and Xie (1999) and Hayn (1995). The second condition ensures that selected entities have a reasonable history as a going concern and the third ensures that the number of entities within each industry classification is not prohibitively small, preventing the situation where there are too few observations to warrant a realistic mean calculation.

Once the population had been defined, a filter was applied to remove observations located outside of the 1st and 99th percentiles from the pooled observations. This

filter was applied specifically to eliminate extreme positive outliers, which could potentially distort the research results. This stems from the design of the study, which limits the downside risk of the valuations, i.e. they cannot be smaller than zero, but does not limit the upside risk of the valuations. Therefore, since the valuation errors could potentially be substantially larger than zero, the risk of distortion is on the upside. However, to prevent a biased outcome the filter was applied on the upper and the lower ends of the pooled observations.[15] The reasoning for this is two-fold. Firstly, excluding extreme observations will prevent the severe distortion of the research results, since the initial analysis indicated the prevalence of a significant number of outliers (Nel, Bruwer & Le Roux, 2013a; Nel, Bruwer & Le Roux, 2013b). Secondly, rational investment practitioners will most certainly exclude these extreme observations when estimating peer group multiples in practice.

Note that the six research questions posed in this study require the data in a certain format. The determination of the optimal industry classification for peer group selection purposes, for example, requires the creation of peer groups (based on four different industry classifications), which are not readily available from the original data set. Since the raw data, i.e. the original form of the data as extracted from the McGregor BFA database, was not ready-for-use for the purpose of answering the six research questions, a substantial amount of work had to be carried out on the raw data to prepare it for this study. To this end, 32 functions were coded in the *R-package* for the preparation and analysis of the data, as well as for the optimisation of the composite multiples models. The outputs from these functions were tested before they were applied to the data. The purpose of coding these functions was three-pronged: Firstly, to prepare the data for data analysis; secondly, to calculate and analyse the valuation errors; and thirdly, to compile composite multiples models. A list of the functions that were coded in the *R-package* and their specific *R-code* are available in Annexures C and D.

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[15]   Note that the truncation of the data set will not eliminate the difference in scale problem related to having large and small entities in the same sample (Durtschi & Easton, 2005; Easton & Sommers, 2003).

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The final population of observations represents approximately 71% of the total number of listed entities on the JSE as at 31 December 2010 and approximately 91% of the market capitalisation of the entities listed on the JSE at the same date, which serves as a fair representation for the conclusions drawn. Although various potential combinations of the market price and value drivers exist, the focus for the purpose of this study was on multiples within each of the five most popular value driver categories, namely earnings, dividends, assets, revenue and cash flows (Nel, 2010; PwC, 2010; Nel, 2009a; Liu *et al.,* 2002b; Cheng & McNamara, 2000). The framework of multiples; i.e. the ratio of the MPVs to the respective value drivers, that was used in the analysis is summarised in Table 2.1.

3.3 STATISTICAL APPROACH

Although various statistical methods were considered for this study, the nature of the data limited the spectrum of methods applicable. Consequently, the key methods applied were PCA, singular value decomposition, Principal Component Regression (PCR) and three optimisation methods, namely the Sum of the Squared Valuation Errors (SSVE), the Sum of the Absolute Valuation Errors (SAVE) and the Median of the Valuation Errors (MVE). The three optimisation methods were applied via three R-based applications, namely *Quadprog*, *lpSolve* and *Rsolnp*. Unfortunately, as discussed in Section 3.3.1 below, given the nature of the data extracted for the purposes of this study, normal regression methods could not be applied. Piecewise, ridge or other nonparametric regression advances may offer interesting alternatives for future research efforts in this regard. These alternatives will, however, require extensive data imputations and are considered to be beyond the scope of this study.

3.3.1 Regression analysis

Given the design of the study, a fair degree of multicollinearity was anticipated. However, this was dealt with effectively through the use of PCA, which nullified kappa readings (measure of multicollinearity) to insignificant numbers. This is indeed one of the key contributions of a PCA-based approach, i.e. it transforms the initial multi-variable data set into uncorrelated combinations (principal components) of the

original independent variables. All of the principal components were therefore independent of each other after transformation. This was followed by PCR, which is ideally suited to highly correlated predictor variables, with plausible results (all the coefficients were positive, the principal components were indeed linearly independent of each other, they were all statistically significant at least at the 95% confidence level and returned R-squared readings of between 0.70 and 0.95). However, the analysis of the residuals of the PCR indicated the violation of various standard Gauss-Markov linear assumptions (Hill, Griffiths & Lim, 2012).

As was evident from the analysis of the diagnostics, the residuals suggest that the data does not follow a normal distribution and does not exhibit a linear pattern. Equally evident was the presence of influential outliers. However, the biggest obstacle was the lack of depth in the South African market. The latter culminates in data limitations, which is a common phenomenon in developing markets (Sehgal & Pandey, 2009; Omran, 2003). Based on market capitalisation, for example, the JSE is small compared to the major securities exchanges in the world (Firer, Ross, Westerfield & Jordan, 2012). There were only 375 entities listed on the JSE in 2013, compared to almost 2 637 entities on the National Association of Securities Dealers Automated Quotations (NASDAQ), for example (World Federation of Exchanges, 2014; Profile, 2011). This is despite the fact that the JSE is rated as the best-regulated exchange in the world, the highest overall ranked exchange in sub-Saharan Africa and the second highest overall ranked exchange among the BRICS countries, surpassed only by China (World Economic Forum, 2013).

Consequently, the data set proved to be unsuitable for normal regression analysis or PCR. Therefore, the market-based approach, which is a popular and well established approach in the international finance literature, was subsequently adopted.

3.3.2   Market-based approach

The market-based approach was introduced into the finance literature by Alford (1992), in a joint research effort between the Massachusetts Institute of Technology

and corporate financiers from Ernst and Young. It has since been refined by scholars from various top academic institutions, including Harvard Business School (Gilson, Hotchkiss & Ruback, 2000), Yale University, the University of California, Los Angeles (Liu *et al.,* 2007; 2002a; 2002b) and others (Nissim, 2011; Minjina, 2008; Dittmann & Weiner, 2005; Berkman *et al.,* 2000; Cheng & McNamara, 2000; Kaplan & Ruback, 1995). The growth in the popularity of the market-based approach as a method to assess the valuation accuracy of multiples can, at least in part, be attributed to the fact that, unlike most theoretical models that are based on simplified realities, it is a realistic, if not near exact, reflection of how multiples are applied in practice. Another benefit of the market-based approach is that it does not rely on the rather cumbersome assumptions of regression analysis. The market-based approach is particularly apt for analysing the relationship between accounting data and market prices, which is the main purpose of this study. In addition, the market-based approach has the ability to evaluate more observations than a standard regression approach, since it does not require the coefficients to remain constant over the entire period between 2001 and 2010.

Consequently, the market-based approach offers a good alternative to PCR and, if applied carefully, could offer valuable insights into the South African market. However, when benchmarking the market price of a share that is listed on the JSE as "correct", the premise of such an approach is that there is some form of market efficiency.

3.3.3   The efficient market hypothesis

The key assumption of the market-based approach is that the accounting variables that are tested in this study carry information content that is relevant to the market price, i.e. the accounting information that is extracted from the financial statements is value relevant. The specific link that is investigated in this study is the one between the market price and multiples, which is derived from the accounting information as contained in the financial statements. The stronger the link is between the market price and a multiple, therefore, the higher the value relevance of the multiple, or the

accounting information that it rests on. The challenge, however, lies in measuring the value relevance of the multiples.

There are various ways of measuring the value relevance of accounting information. The basic premise, however, is that, in order to be value relevant, accounting information must have the ability to impact valuations (Zhang, 2000). From a valuation perspective, one would be inclined to argue that, in order to be valuable, accounting information must be able to influence the composition of valuation models such as multiples. Equally important is the extent to which investment practitioners require accounting information to inform their future views on entity shares. If there is a strong correlation between accounting information and the information used by investment practitioners to value entities and their shares, especially if the correlation is consistent over a longer time period, it would carry a high level of value relevance.

Note in this respect that the value relevance of accounting information does not necessarily remain constant over time. Consider, for example, the South African Institute of Chartered Accountants' adoption of International Financial Reporting Standards (IFRS) in January 2005. The adoption of these universal financial reporting standards could impact on the value relevance of accounting information. The ensuing reduction in information asymmetry at the entity level could potentially diminish the occurrence of accounting and earnings manipulation. Unfortunately, the available literature on the value relevance of accounting information, especially pertaining to emerging markets, is limited. However, Bao & Chow (1999) found evidence suggesting that the value relevance of accounting information in China increased over time. Similar results were initially found by Negash (2008) in the South African market, although scale issues prevented the rejection of the hypothesis that no improvement in value relevance of accounting information occurred over time.[16]

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[16] Since the focus of this study is on the proper construction of multiples, a more detailed analysis of the various avenues of financial reporting-based research, such as the impact of the adoption of IFRS and other liberalisation-related research pertaining to ownership and institutional restructuring is not elaborated on here.

Information inefficiencies are not limited to the entity level. Informational issues also pertain to the market microstructure environment in which these entities' shares trade. Market microstructure theory, as a sub discipline of finance, has attracted the keen interest of researchers concerning market transparency, in particular. Issues in this respect include, but are not limited to, information dissemination and disclosure concerns regarding the trading process itself. Asymmetric inter-market trade disclosures induce order flow migration, which, in turn, could affect liquidity and trading costs (Amihud, Mendelson & Lauterbach, 1997).

As the second oldest exchange in Africa, the microstructure of the JSE has evolved considerably over time. The globalisation of, and the ensuing liberalisation drive in, emerging markets have attracted substantial capital inflows. The JSE is no exception. The average JSE liquidity levels were approximately 48% over the past decade, which is negligible in comparison to those of the developed markets, such as the NASDAQ, for example, with average liquidity levels of approximately 557% over the same period (World Federation of Exchanges, 2014). However, it is a vast improvement from the 5.5% liquidity level in 1993, prior to the liberalisation of the South African market in 1994. In addition, trade volumes increased from 674 814 to 26 504 219 between 1993 and 2011 (Southern African Venture Capital and Private Equity Association, 2014). These changes were, at least in part, attributable to changes in the JSE market microstructure.

Therefore, market microstructure theory, via its impact on the level of information efficiency, has a bearing on this study since it is linked to decisions regarding investments, financing and capital structure. However, the intention of this study is not to conduct a comprehensive overview of market microstructure theory and it is therefore not elaborated on in more detail here.

Given the design of this study, the degree of value relevance can be measured by the ability of the multiples models to predict actual share prices. Therefore, a model that has the ability to offer an accurate estimate of actual share prices will carry a higher degree of value relevance compared to models that offer less accurate estimates of actual share prices.

However, assuming a high degree of market efficiency might be presumptuous, especially in the case of the strong form. A strong form of market efficiency is based on the ability of the market to fully discount all the information, including insider information, relevant to a particular share, immediately in its share price. This is, however, not a common phenomenon. Under the assumption of the strong form of efficiency, market participants are unable to beat the market in the absence of asymmetric information. The other two forms of market efficiency are the semi-strong form and the weak form, both of which are far more common (Fama, 1970). Under the semi-strong form of efficiency, market prices fully discount all the relevant information that is publicly available. The lowest level of market efficiency is known as the weak form of efficiency, which means that the market is only able to discount relevant historical price information into share prices.

What level of market efficiency does the JSE exhibit in the South African market? The literature contains conflicting evidence in this regard. On the one end of the spectrum, there are researchers who detect evidence of a semi-strong form (Smith, 2008; Jefferis & Smith, 2005; Magnusson & Wydick, 2002). The opposing view is that the JSE does not exhibit a semi-strong form of market efficiency (Watson & Rossouw, 2012; Glass & Smit, 1995; Philpott & Firer, 1995). However, these studies all employed different methodologies, which inhibits an all-encompassing confirmation regarding the semi-strong form of the JSE. Perhaps the most apt description of the market efficiency form of the JSE is that, although there is no conclusive evidence that it is not efficient in the semi-strong form, it does exhibit pockets of efficiency (Philpott & Firer, 1995).

The form of efficiency of the JSE is important since entity failures undermine investor confidence in the market. Of particular importance in this respect is the role of accounting information and its relationship with share prices, which is a key concept investigated in this study. When this link is dishonoured or disrupted, investors tend to disengage from the market, which results in falling share prices and credit-rating downgrades, often to junk status (Agrawal & Chadha, 2005).

Fortunately, the specific form of market efficiency does not affect this study, which focuses on value relevant accounting information and its relationship with market

prices. The relevant assumption, in this case, is that market prices are driven by investor sentiment. Therefore, share prices are determined by the interaction between market forces, i.e. supply and demand. This study does not rest on the premise that market prices are unbiased reflections of the intrinsic value of entity shares, nor that intrinsic value is observable.

However, for the purpose of this study, the market prices, as reflected on the JSE, are benchmarked as "correct", which assumes some form of market efficiency. Value estimates, based on various multiples, that represent a derivation of accounting information, are subsequently compared to these benchmarked prices. The size of the discrepancies observed between the value estimates and market prices serves as an indication of the multiple's error relative to the benchmark. Obviously, smaller errors would be preferred, since they suggest a more accurate valuation multiple, and *vice versa*.

3.4   THE MARKET-BASED MODEL

3.4.1   Single factor multiples model

Investment practitioners typically calculate an industry average multiple and multiply it by a specific entity's value driver, such as PAT, for example, to value an entity's equity (Goedhart *et al.,* 2005). This is in line with multiples-based valuation theory, which holds that the Actual equity value (V_{it}^{e}) of an entity (i) at a given point in time (t) is equal to the product of an Actual equity-based multiple (λ_{t}^{e}) and a specific Actual value driver (α_{it}) at that specific point in time, so that

$$V_{it}^{e} = \lambda_{t}^{e} \cdot \alpha_{it} \tag{3.1}$$

The objective of the single factor multiples model is to quantify the ability of Equation (3.1) to approximate actual share prices on the JSE. After extracting and screening the data from the McGregor BFA database according to the criteria stipulated

in Section 3.2, an out-of-sample equity-based peer group multiple ($\hat{\lambda}_{pt}^{e}$) is estimated for each entity by calculating the harmonic mean of all the other remaining entities in a particular peer group. The P/PAT peer group multiple estimate for entity A, for example, in a peer group that contains entities A to E, would therefore be equal to the harmonic mean of the P/PAT multiples of entities B to E. The harmonic mean was used to estimate the peer group multiples since it avoids the upward bias of the arithmetic mean and is regarded as a viable and unbiased estimator (Dittman & Maug, 2008; Bhojraj & Lee, 2002; Liu *et al.,* 2002b; Beatty *et al.,* 1999).

The selection of the peer group was based on the McGregor BFA SEC level classification, unless specifically stated otherwise. The application of an industry-specific approach to multiples is well established by research (Nel *et al.,* 2013b; Nel, 2009a; 2009b; Goedhart *et al.,* 2005; Liu *et al.,* 2002a; Fernández, 2001; Barker, 1999). An Equity value prediction ($\hat{V}_{it}^{e}$) is calculated by multiplying each entity's Estimated equity-based peer group multiple ($\hat{\lambda}_{pt}^{e}$) by the entity's Actual value driver (α_{it}):

$$\hat{V}_{it}^{e} = \hat{\lambda}_{pt}^{e} \cdot \alpha_{it} \tag{3.2}$$

Subtracting Equation (3.1) from Equation (3.2) produces (3.3) for the calculation of the error margin (valuation error):

$$\hat{V}_{it}^{e} - V_{it}^{e} \tag{3.3}$$

It is anticipated that (3.3) will not be independent of value and that the size of an individual entity's equity value may distort the size of the valuation errors. Therefore, (3.3) is expressed proportionally to V_{it}^{e} to improve the efficacy of the estimated peer group multiple (Beatty *et al.,* 1999). The standardised form of (3.3), ε_{it}, is therefore expressed in absolute terms, proportionally to V_{it}^{e}, so that

$$\varepsilon_{it} = \left| \frac{\hat{V}_{it}^{e} - V_{it}^{e}}{V_{it}^{e}} \right| \qquad (3.4)$$

Given the nature of the construction of multiples, on which the methodology applied throughout this dissertation is based, the scale problem encountered when applying cross-sectional regressions and the accompanying potential distortion of the intercept and the coefficients, do not pose a problem here. This stems from the fact that multiples are constructed by deflating market price with various, similarly-sized value drivers.[17]

Note that Equations (3.1) and (3.2) refer to equity-based multiples in particular. The valuation of equity by means of entity-based multiples will require the use of similar entity-based equations. Equation (3.1) is adjusted by replacing the equity-based multiple (λ_t^e) with an entity-based multiple (λ_t^n) and Debt (d) is deducted from the entity value to obtain the equity value:

$$V_{it}^{e} = \lambda_{t}^{n} \cdot \alpha_{it} - d \qquad (3.5)$$

The equity value prediction ($\hat{V}_{it}^{e}$) is calculated by multiplying each entity's Estimated entity-based peer group multiple ($\hat{\lambda}_{pt}^{n}$) by the entity's Actual value driver (α_{it}), and deducting d from the entity value prediction ($\hat{\lambda}_{pt}^{n} \cdot \alpha_{it}$):

$$\hat{V}_{it}^{e} = \hat{\lambda}_{pt}^{n} \cdot \alpha_{it} - d \qquad (3.6)$$

As in the case of equity-based multiples, subtracting Equation (3.5) from Equation (3.6) produces (3.3) for the calculation of the error margin:

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[17] A similar approach was adopted by Easton and Sommers (2003), who opted to mitigate the scale problem by deflating the dependent and independent variables. As Negash (2008) correctly points out, however, in the case of Easton and Sommers (2003) the deflation transforms the model into a nonlinear one, which obscures the interpretation of the dependent variable.

$$\hat{V}_{it}^{e} - V_{it}^{e} \tag{3.3}$$

The absolute valuation errors of the multiples are subsequently pooled for all the entity years.[18] The use of absolute numbers prevents the netting of positive and negative valuation errors, which may result in artificially low measures of central tendency and dispersion, such as the mean, for example. The multiple that produces the most accurate equity valuation will be the multiple with the lowest valuation error, which generally equates to the multiple with the tightest distribution around a central value, such as the mean (Pratt, 2005). Several measures of central tendency and dispersion will be used to analyse the pooled observations. These include the mean, median, SD, CV, IQR, MAD and the CMAD, which allows comparison with various international studies in this regard (Herrmann & Richter, 2003; Lie & Lie, 2002; Liu *et al.,* 2002a; Kim & Ritter, 1999; Kaplan & Ruback, 1995).

3.4.2 Composite multiples models

For the purpose of investigating the valuation accuracy of composite multiples models, the equation for the equity value prediction becomes the following:

$$\hat{V}_{it}^{e} = \sum_{j=1}^{k} \beta_{jt} \cdot \hat{\lambda}_{jpt}^{e} \cdot \alpha_{jit} \tag{3.7}[19]$$

where $\hat{V}_{it}^{e}$ is the predicted equity value of entity i at time t and $\hat{\lambda}_{jpt}^{e} \cdot \alpha_{jit}$ represents each single factor equity value prediction (j) that is included in the composite multiples model. The optimal number of single factor multiples that is catered for in the composite model will depend on the empirical results. It is envisaged that these

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[18] Functions for the calculation of ε_{it} and the statistical analysis thereof were developed in the *R-package* (R Core Team, 2013), an open source programming language that lends itself to statistical analysis and graphics.

[19] As with the cross-sectional analysis, Equation (3.7) refers to equity multiples in particular. The valuation of equity by means of entity multiples will require adjusting Equation (3.7) by deducting debt from the right hand side of the equation.

multiples will be drawn from various value driver categories, which may include earnings, dividends, assets and cash flows. Although a high level of multicollinearity amongst the respective value drivers in each of these categories is expected, careful statistical analysis by means of PCA and PCR may mitigate such an occurrence. The β-value refers to the corresponding weights for each of the single factor multiples, which will be determined by optimisation applications in the *R-package*.

The assumptions are that $0 \leq \beta_{1t}, \ \beta_{2t}, ..., \beta_{kt} \leq 1$

and

$$\sum_{j=1}^{k} \beta_{jt} = 1$$

The composite multiples model's predicted equity value will therefore encapsulate the weighted average of the predicted values of the respective single factor multiples. These weight allocations will be obtained from optimisation applications in the *R-package*.

As with the cross-sectional analysis, the standardised absolute deviation (ε_{it}) is expressed proportionally to V_{it}^{e}, therefore

$$\varepsilon_{it} = \left| \frac{\hat{V}_{it}^{e} - V_{it}^{e}}{V_{it}^{e}} \right| \qquad (3.4)$$

A number of methods were considered for the comparison of the valuation performance of the composite models *vis-á-vis* the single factor models. Among the alternatives considered were R-based PCA, PCR, singular value decomposition, *Quadprog*, *lpSolve,* as well as *Rsolnp*. Unfortunately, the nature of the data rendered many of these alternatives unsuitable for the purposes of this study. Consequently, the components of the composite models were weighted based on the three mathematical optimisation applications, namely *Quadprog*, *lpSolve* and *Rsolnp*. The

Quadprog application optimises the weight allocations based on the objective of minimising the SSVE. However, the underlying principle of the SSVE approach is similar to that of linear regression, which academic researchers generally favour due to its simplicity and the ample software programmes available in support of it. Valuation theory, however, suggests that very few, if any, relationships among multiples are linear (Damodaran, 2006a; Yee, 2005). Therefore, despite the popularity thereof, the SSVE-based results were deemed less reliable. Consequently, the *lpSolve* application, which optimises the weight allocations based on the objective of minimising the SAVE, was used as the main mathematical optimisation tool. Therefore, the weights that were allocated to the constituents of the composite models were drawn from the results of the *lpSolve* application. The third application, *Rsolnp*, which optimises the weight allocations based on the objective of minimising the median valuation error, was used to validate the results that were obtained from the *lpSolve* application. The latter results also afford one the opportunity to compare the results with that of studies which applied median-based valuation errors in the USA and European markets.

Note that the methodology described in Section 3.4 offers the generic, market-based approach that was adopted in this study. Where applicable, this approach was adjusted and elaborated on to accommodate the investigation of the research questions specific to each of Chapters 4 to 9.

CHAPTER 4

THE IMPACT OF INDUSTRY CLASSIFICATION-BASED PEER GROUP SELECTION ON THE VALUATION ACCURACY OF MULTIPLES

4.1   INTRODUCTION

The objective of this study is to establish whether composite models produce more accurate valuations than single factor multiples models. In order to do so, it is necessary to construct both optimal composite models and optimal single factor multiples models. Since composite multiples models are constructed from single factor multiples models, it makes sense to first investigate the composition and valuation accuracy of single factor multiples models. Once the most accurate single factor multiples models have been identified, their valuation accuracy can be compared to that of the composite multiples models.

In order to assess the valuation accuracy of single factor multiples it is important to understand that multiples are essentially relative valuations. The latter implies that multiples value assets relative to how other, similar assets are valued in the market. This is the first, and probably the most challenging, aspect to consider when performing multiples-based valuations, i.e. how to identify an appropriate peer group of entities. Peer group selection, which is the focus of Chapters 4 and 5, can be based on industry classification or on entities with similar valuation fundamentals. The former is investigated in Chapter 4, while the latter is investigated in Chapter 5.

The focus of Chapter 4 is, therefore, on the ability of peer group selection to increase the valuation accuracy of multiples. The objective is to answer research question one by validating H1, which postulates:

H1:   Multiples whose peer group selection is based on narrower industry classifications, i.e. smaller groups of more homogeneous entities, offer higher degrees of valuation accuracy *vis-á-vis* multiples whose peer group selection

is based on wider industry classifications, i.e. larger groups of more heterogeneous entities.

A careful study of the emerging market literature would reveal that no empirical support currently exists in this respect. In fact, there is currently no best practice guide for the proper construction of multiples in emerging markets. From an academic perspective, two of the most widely used South African finance textbooks offer little guidance on the issue of peer group selection (Firer *et al.*, 2012; Correia *et al.*, 2011). These are not merely academic considerations. Theory should lead practice, especially in applied disciplines such as accounting and equity valuations (Nissim & Penman, 2001). Unfortunately, research conducted in South Africa by Nel (2010; 2009b) indicates that a gap exists between theory and practice in the application of equity valuation and multiples, in particular. Therefore, it seems at least plausible that the assumption of the accuracy of an approach adopted in practice merely because of its logical nature may not be underpinned by empirical evidence.

Peer group selection that is based on a narrower industry classification may make sense intuitively, since more homogeneous entities are grouped together. However, it may be impractical in some cases. For example, depending on the number of entities contained in a certain industry classification, a wider industry classification may actually produce more accurate valuations than a narrower one. An increase in valuation accuracy may also occur in an inconsistent manner. For example, while narrowing an industry classification from IND to SUP may result in an increase in valuation accuracy, since it groups more homogeneous entities together, further narrowing from SUP to SEC, which supposedly results in an even more homogeneous group of entities, may actually result in a decrease in valuation accuracy, before improving again when narrowing the industry classification further from SEC to SUB. In this case, applying a SEC industry classification by default will result in a suboptimal valuation performance in terms of valuation accuracy.

One may also be inclined to ask whether industry classification matters, i.e. does a narrower industry classification result in a substantial increase in valuation accuracy or is the valuation accuracy differential immaterial? How would one be able to select

an appropriate industry classification without insight into the magnitude of an increase in valuation accuracy that an empirical perspective may offer in this regard? The latter seems especially plausible in an emerging market such as South Africa, due to the limited depth of its equity market. It therefore seems imperative that empirical evidence exists in support of common valuation practices. It is hoped that the investigation in Chapter 4 will provide insight into these industry classification-related issues.

Therefore, the primary aim is to establish whether peer group selection by narrower industry classification will increase the valuation accuracy of multiples. The secondary aim is to determine the potential improvement in valuation accuracy that industry narrowing may offer *vis-à-vis* wider industry classifications. The third aim is to determine the optimal industry definition for peer group selection purposes. The results of the research conducted in Chapter 4 offer an emerging market perspective on an optimal peer group selection strategy that is based on industry classification. The research results present an important theoretical platform for the optimal construction of multiples in the remaining chapters of this dissertation.

4.2   LITERATURE REVIEW

Peer group selection plays a pivotal role in multiples-based valuations (Nel *et al.,* 2013a; 2013b; Bhojraj & Lee, 2002; Eberhart, 2001; Fenn & Cole, 1994; Lang & Stulz, 1992; Fuller & Kerr, 1981). In practice, investment practitioners generally start with an industry multiple and then apply adjustments of 10 - 20% to reflect differences in, *inter alia,* growth rates, profitability and quality of earnings (Kim & Ritter, 1999). However, this approach is clearly subjective and lacks a sound empirical basis. Unfortunately, very little theoretical guidance is available for peer group selection in practice, especially in emerging markets.

In theory, there are two approaches to peer group selection. It is either based on a set of comparable entities or comparable transactions (Stowell, 2010). The comparable entities method is based on the assumption that relatively homogeneous entities reside in the same industry or that the magnitude of their fundamental

variables are relatively similar. Since these entities are thought to have similar financial and operational characteristics, they are expected to have similar prospects for three key fundamental variables that drive value, namely profitability, growth and risk. The method which relies on the selection of comparable transactions, which is typically used for valuing merger and acquisition deals, selects historical corporate transactions in the same industry or country as comparables (Pratt, 2005). However, as a result of data limitations, the comparable transactions method is less appropriate for statistical analysis. Consequently this study focuses on peer group selection that is based on comparable entities.

Statistical logic would suggest that not one, but several, comparable entities should be selected. The logic is that the SD of the valuation errors, when selecting one entity, *vis-à-vis* the SD when selecting several entities, will be higher (Alford, 1992). Despite the wide application thereof in practice, very little theory is available on how, and why, certain comparable entities should be selected in certain circumstances. There are two schools of thought in this regard (Bhojraj & Lee, 2002). The first school of thought defines comparable entities simply as entities in similar industries. Consequently, since entities in similar industries display similar risk and earnings growth characteristics, comparable entities are selected based on industry classification (Damodaran, 2006a; Alford, 1992). The second school of thought argues that a comparable entity set should be compiled based on valuation fundamentals (Foushee *et al.,* 2012; Ivashkovskaya & Kuznetsov, 2007; Dittmann & Weiner, 2005; Goedhart *et al.,* 2005). The valuation fundamentalists favour the selection of comparable entities on the basis of similar variables such as profitability, growth and risk, instead of industry classification. The focus of Chapter 4 is on the first school of thought, i.e. where the peer group (the set of comparable entities) is selected based on industry classification. The second school of thought will be investigated in Chapter 5.

Most existing studies build on the comparable entity principle work of Alford (1992), who found that selecting comparable entities based on 3-digit Standard Industry Classification (SIC) codes is reasonably effective. According to Alford's research results, a narrower industry classification improves the valuation accuracy of multiples, but with diminishing significance as the industry definition is refined further.

Alford also noted that, when selecting comparable entities based on industry classification, the valuation accuracy is greater for larger entities than for smaller entities. However, his research was limited to USA entities and covered only three years, namely, 1978, 1982 and 1986.

In a similar study on USA and European entities, Schreiner (2007) found that forming a smaller, but more homogenous peer group; i.e. by narrowing the industry classification from 1-digit to 2-digit to 3-digit industry codes, improved the valuation accuracy of multiples. This study included accrual-, book value- and cash flow-based multiples. When employing a median absolute valuation error and a 15% Fraction Error (FRE) range, the empirical results indicated that a narrower industry classification; i.e. narrowing the industry classification from 1-digit to 3-digit industry codes, increased valuation accuracy, on average, by 8.60% and 17.17%, respectively (Schreiner, 2007).

Henschke and Homburg (2009) obtained similar results when they tested the impact of a narrower industry classification on the valuation accuracy of USA-based entities over the period 1986 to 2004. They compared, among others, the valuation accuracy of four multiples, namely, price-to-book value, price-to-Compustat-earnings, price-to-forecast-earnings and price-to-Institutional Brokers Estimation System (IBES)-earnings. Their research results indicated that, for 75.00% of the observations, a narrower industry classification resulted in an increase in valuation accuracy.

Research conducted by Berkman e*t al.* (2000) in New Zealand presented evidence to the contrary. However, their evidence was based on a small sample of 45 newly listed entities on the New Zealand Stock Exchange. The authors also conceded that their findings were based on data that was difficult to obtain in a thinly traded capital market, which may have obscured the results.

Note that the focus in Chapter 4 is on peer group selection based on industry classification in particular. Peer group selection could be further refined to consider additional factors such as valuation fundamentals and industry concentration, either in isolation or in conjunction with industry classification. However, while the former is an *ex ante* model consideration, the latter is not. In addition, although industry

concentration offers insight into market characteristics that may impact on an entity's earnings, it is not, in itself, an appropriate basis for peer group selection. Therefore, although industry concentration, as an intra-industry consideration, has attracted considerable attention in the literature, it is not elaborated on in the analysis in Chapter 4.[20]

Consequently, the focus in Chapter 4 is on a peer group selection strategy that is based on industry classification in particular. Although the majority of evidence in this respect indicates that a narrower industry classification results in an increase in valuation accuracy, the international literature focuses on developed economies, while shedding little light on emerging markets. No such research has, for example, yet been conducted in South Africa. Consequently, the research conducted in Chapter 4 aims to address the lack of empirical evidence in this regard and to add an emerging market perspective to the existing literature.

4.3   DATA SELECTION

The number of observations differed for each multiple and industry classification, depending on how well the multiples satisfied the criteria stipulated in Section 3.2. As a result, the multiples have different population sizes over different industry classifications, varying between 759 and 2 747 observations each. The total population of multiples included 125 637 observations, which were used to construct the 16 multiples contained in Table 4.1.

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[20] The evidence suggests that entities that operate in less concentrated industries command a concentration premium, which is attributed to the fact that such entities are exposed to higher levels of risk as a result of their greater innovation drive (Hou & Robinson, 2006). Conversely, entities that operate in highly concentrated industries earn lower returns, possibly as a result of high barriers to entry in concentrated industries, which insulate these entities from the risk of financial distress. What makes the findings of Hou and Robinson (2006) particularly interesting is that they contradict the controversial Schumpeter hypothesis, which states that the ability of monopolistic entities to earn monopoly profits is a precondition for innovation. However, the evidence in support of, and against, the Schumpeter hypothesis, and the related issue of industry concentration, are *ex-post* model considerations, and therefore, not elaborated on here.

4.4   RESEARCH METHODOLOGY

The premise of the research methodology applied in Chapter 4 rests on the ability of valuations based on Equation (3.1) to approximate actual share values. The generic approach described in Chapter 3 is consequently adjusted to accommodate the verification of H1. An out-of-sample peer group multiple ($\hat{\lambda}_{pt}^{e}$) for each entity is estimated by calculating the harmonic mean of all the other remaining entities in the industry classification category concerned for that specific multiple (refer to Section 2.5.3 for a discussion of the harmonic mean). The estimated SUB P/GP multiple for entity A, for example, in a SUB that contains entities A to E, will be equal to the harmonic mean of the P/GP multiples of entities B to E.

Although it may seem necessary to pursue a more diligent peer group selection process by also considering factors such as entity size and expected growth rates, the primary focus of Chapter 4 is to establish the impact of a narrower industry classification on the valuation accuracy of multiples. To this end, peer group selection will be refined through the four McGregor BFA industry classification categories, namely, IND, SUP, SEC and SUB.

The remainder of the analysis in Chapter 4 adopts the generic approach as set out in Section 3.4.1, i.e. Equations (3.1) and (3.2) are applied to eventually arrive at the standardised form of (3.3), where ε_{it} is expressed proportionally to V_{it}^{e} in Equation (3.4):

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

The *R function CalcVEVds* was written to implement Equation (3.4). The output of *CalcVEVds* contains 64 pools of valuation errors (ε_{it}), i.e. four different pools of valuation errors for each of the 16 multiples. These ε_{it} were analysed with the use of

the *R function AnalyseVE*. Each pool of valuation errors will therefore be multiple-specific and will be based on one of the four industry classifications. This affords one the opportunity to assess the relative valuation performance of each multiple, whose peer group was based on four different industry classifications.

The optimal industry classification for each multiple, i.e. the industry classification that produces the most accurate equity valuation, will be the one with the lowest summarised valuation error. To this end, four measures of location were used to analyse the pooled observations, namely the mean, the 25th Percentile (P25), the median and the 75th Percentile (P75). An additional two measures, namely the 15% FRE (FRE 0.15) and 25% FRE (FRE 0.25) ranges, were employed to gauge the impact of a narrower industry classification on the valuation accuracy of multiples. These two FRE ranges measure the percentage of valuation errors below 0.15 and 0.25, respectively. Therefore, a higher summarised score (percentage) would indicate an increase in valuation accuracy, as opposed to the first four summarised measures, where a lower score indicates an increase in valuation accuracy. This allows comparison with various international studies (Herrmann & Richter, 2003; Lie & Lie, 2002; Liu *et al.,* 2002a; Kim & Ritter, 1999; Kaplan & Ruback, 1995).

The performance of the multiples over the four industry classifications was evaluated by comparing the locality and dispersion of their respective valuation errors. An Industry Value Chain (IVC) was subsequently created, which indicates the extent to which the valuation accuracy of multiples improved as the industry classification was narrowed. The IVC indicates the Potential percentage improvement (IMP) in valuation accuracy that may be secured by substituting a wider industry classification with a narrower one.

4.5   EMPIRICAL RESULTS

This section deals with the locality and dispersion of the valuation errors of the 16 multiples. The key measures used to calculate the locality and the dispersion were the mean (central tendency), the P25, the median (central tendency), the P75 and

the FREs 0.15 and 0.25.[21] These measures are contained in Table 4.1 and are also presented, in part, in the form of boxplots in Figures 4.3 and 4.4.

4.5.1   Interpreting boxplots

Boxplots, also known as box and whisker plots, offer a summary of the descriptive nature of a data set. They depict the shape of the data set's distribution, its central value and variability. Typical measures displayed include extreme values (maximum and minimum values), the upper and lower quartiles and the mean and the median. The boxplots in Figure 4.1 and Figure 4.2 represent the valuation accuracy of the P/EBITDA multiple, whose peer groups are based on four different industry classifications, namely IND, SUP, SEC and SUB. Note that Figure 4.1 depicts the complete range, while Figure 4.2 depicts a limited range, i.e. a zoomed version of Figure 4.1.

Note from Figure 4.2 that the data set in the box area is split into quartiles. The box area, which stretches from the lower edge of the box, i.e. the first quartile to the upper edge of the box, i.e. the third quartile, reflects the IQR. Within the box area, a horizontal white line indicates the second quartile, i.e. the median, of the data set.

Two vertical lines (whiskers) extend from the top and bottom of the box area. The bottom whisker runs from the first quartile to the smallest non-outlier in the data set, and the top whisker runs from the third quartile to the largest non-outlier. The ends of the whiskers are typically positioned at the lowest and highest data points that reside within 1.5 times the IQR, measured from the first quartile and the third quartile, respectively. However, since the means (depicted by asterisks) in Figure 4.1 are not visible when the ends of the whiskers are set at 1.5 times the IQR, they are, for illustrative purposes, positioned at five times the IQR. Note that the smallest non-outlier cannot be smaller than zero, while the largest non-outlier is unbounded, which naturally positions the boxes closer to the end of the bottom whiskers. Usually,

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[21]   The 5th, 10th, 90th and 95th Percentiles, although not shown here, rendered similar results to that of the 25th and 75th Percentiles.

observations that are located at a greater distance from the median than 1.5 times the IQR are regarded as outliers and are depicted as bubbles.
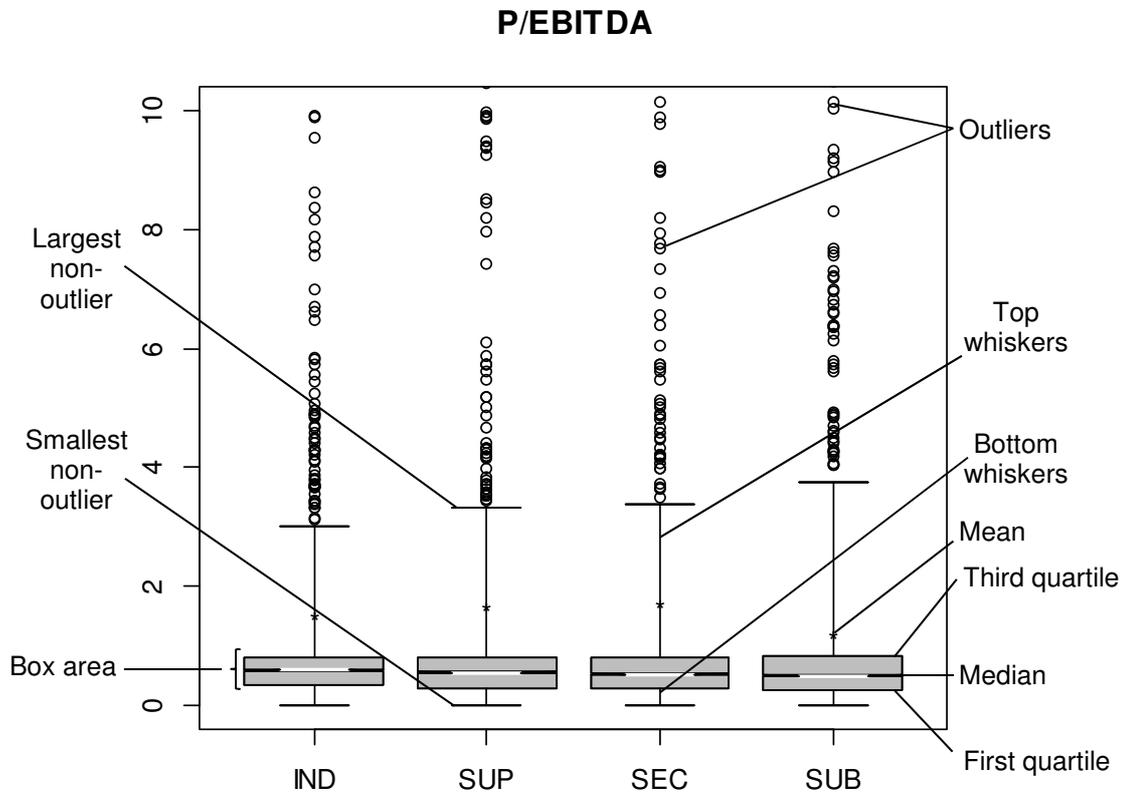
P/EBITDA

Figure 4.1: Valuation accuracy of P/EBITDA multiple over four industry classifications (complete range)

From Figure 4.1, one is able to glean the following regarding the data set: Firstly, the data set contains a number of outliers. Secondly, the mean increases as the industry classification is narrowed from IND to SEC, but decreases when the industry classification is narrowed from SEC to SUB. Thirdly, the data set is positively skewed. This is evident from the boxes that are located substantially closer to the smallest non-outliers than to the largest non-outliers.

Although the reduced scaling of the boxes in Figure 4.1 accommodates the outliers and the means, it inhibits a more detailed analysis of the central 50% of the observations (the boxes). A more detailed analysis of the box areas requires the demarcation of a limited range for the boxplots. Subsequently, in Figure 4.2, the scaling is adjusted to accommodate a more detailed analysis of the box areas.
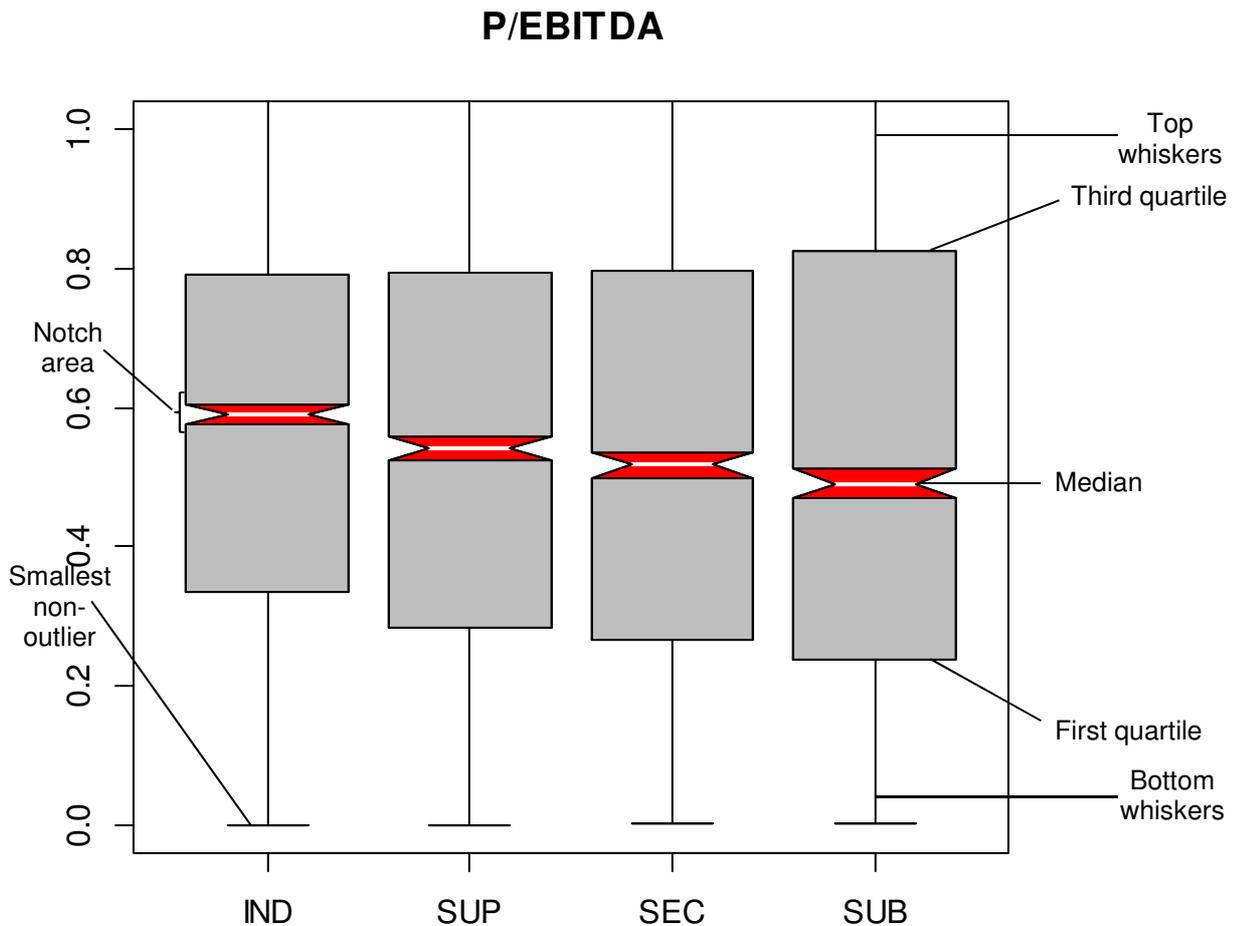
P/EBITDA

Figure 4.2: Valuation accuracy of P/EBITDA multiple over four industry classifications (limited range)

Note from the zoomed illustration in Figure 4.2 that the outliers, means and the largest non-outliers are no longer visible. Instead, the focus is now on the box areas. From Figure 4.2, it is evident that the boxes are notched (red indents), which means that the area around the median is indented. The notches allow statistical inference and offer a rough guide to the statistical significance of differences in medians. If the notches of two data sets do not overlap, this suggests that the difference in their respective medians is statistically significant at the 95% confidence level. From Figure 4.2, one is able to glean the following: Firstly, as the industry classification is narrowed from IND through to SUB, the median declines. In practical terms this means that the P/EBITDA multiple becomes more accurate. Secondly, the notches between the IND and SUP industry classifications do not overlap. Therefore, the decline in the median when narrowing the industry classification from IND to SUP is statistically significant at the 95% confidence level. Thirdly, since the notches of SUP

and SEC and SEC and SUB, respectively, overlap, the declines in their respective medians, when narrowing the industry classification from SUP to SEC and from SEC to SUB, are not statistically significant.

4.5.2   Descriptive statistics

The valuation performance of the 16 multiples was compared over various industry classifications in order to ascertain whether narrower industry classifications resulted in more accurate valuations. In total, 64 pools of valuation errors were estimated, based on four industry classifications, namely, IND, SUP, SEC and SUB. As is evident from Table 4.1 and the boxplots in Figure 4.3, the number of entity year observations (N) declined as the industry classification was narrowed from IND through to SUB, which had a bearing on the mean and the measures of dispersion. The boxplots in Figure 4.3 and Figure 4.4 appear in order of performance, based on the median absolute valuation error; i.e. the multiples are ranked from those with the highest increase in valuation accuracy, to those with the lowest increase in valuation accuracy. Note that the notches in the boxplots in Figure 4.3 and Figure 4.4 approximate 95% confidence levels around the respective medians, which allows statistical inference (McGill, Tukey & Larsen, 1978).

The measures of locality are sensitive to outliers (depicted as bubbles above the top whiskers in Figure 4.3), of which there were quite a few.[22] Apart from the effect that outliers had on the measures of locality and dispersion *per se*, the impact was magnified within the smaller samples; i.e. within the more narrowly defined industry classifications, which may partly explain why the mean offered inconsistent results.

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[22]   The interval parameters for the top and bottom whiskers in Figure 4.3 are [P75 + 5 (P75 - P25); P25 - 5 (P75 - P25)]. The observations located outside these interval parameters are flagged as outliers. Note that the outliers occur only above the top whiskers in Figure 4.3.

Table 4.1: Absolute valuation errors when the industry classification is narrowed: Descriptive statistics

	N	Mean	P25	Median	P75	FRE 0.15	FRE 0.25
			P/GP				
IND	2261	**1.2086**	0.3229	0.5801	**0.8271**	0.1176	0.1955
SUP	2228	1.2809	0.2875	0.5589	0.8449	0.1355	0.2127
SEC	2097	1.5850	0.2754	0.5277	0.8372	0.1388	0.2265
SUB	1683	1.6072	**0.2684**	**0.5201**	0.8834	**0.1450**	**0.2365**
			P/EBITDA				
IND	2393	**1.6314**	0.3357	0.5971	**0.8284**	0.1045	0.1776
SUP	2376	1.7388	0.2764	0.5527	0.8338	0.1317	0.2252
SEC	2277	2.2797	0.2673	0.5317	0.8344	0.1401	0.2328
SUB	1831	1.7757	**0.2418**	**0.5116**	0.8672	**0.1524**	**0.2561**
			P/EBIT				
IND	2330	2.4075	0.3097	0.5578	0.8330	0.1180	0.1983
SUP	2313	2.7723	0.2445	0.5180	0.8351	0.1587	0.2559
SEC	2215	2.7891	0.2312	0.4885	**0.8210**	0.1648	0.2655
SUB	1789	**1.9320**	**0.2195**	**0.4880**	0.8464	**0.1738**	**0.2778**
			P/PAT				
IND	2173	2.6109	0.2682	0.5498	0.8556	0.1275	0.2287
SUP	2157	2.9193	0.2291	0.5127	0.8487	0.1572	0.2703
SEC	2059	2.7160	**0.2220**	0.4890	**0.8393**	0.1622	**0.2749**
SUB	1649	**1.7783**	0.2273	**0.4853**	0.8642	**0.1656**	0.2741
			P/PBT				
IND	2215	2.8513	0.2548	0.5410	0.8572	0.1418	0.2470
SUP	2198	3.3114	0.2211	0.5194	0.8424	0.1724	**0.2784**
SEC	2099	3.0565	0.2228	0.4844	**0.8360**	0.1701	0.2758
SUB	1677	**1.8166**	**0.2204**	**0.4705**	0.8566	**0.1777**	0.2755
			P/HE				
IND	2225	1.7350	0.1839	0.3853	0.7263	0.2090	0.3384
SUP	2209	1.6420	0.1704	**0.3668**	0.7329	0.2205	0.3603
SEC	2110	**1.3976**	**0.1666**	0.3676	**0.7068**	**0.2242**	**0.3630**
SUB	1704	1.7731	0.1686	0.3770	0.7356	0.2224	0.3568
			P/TA				
IND	2747	**1.2581**	0.4070	0.6938	**0.8932**	0.0764	0.1405
SUP	2727	1.7611	0.3710	0.6662	0.8938	0.0895	0.1624
SEC	2650	2.1060	**0.3358**	0.6365	0.9036	**0.1140**	**0.1864**
SUB	2224	1.8895	0.3376	**0.6242**	0.9001	0.1097	0.1808
			P/IC				
IND	2745	**1.2480**	0.4386	0.6997	**0.8967**	0.0769	0.1308
SUP	2725	1.5371	0.3859	0.6871	0.9055	0.0855	0.1483
SEC	2649	1.8597	**0.3575**	0.6597	0.9164	**0.1023**	**0.1725**
SUB	2223	2.0784	0.3652	**0.6441**	0.9129	0.0994	0.1615
			P/BVE				
IND	2467	**1.4504**	0.3793	0.6833	**0.9163**	0.0965	0.1585
SUP	2447	2.1727	0.3526	0.6756	0.9197	0.1005	0.1737
SEC	2356	2.8868	0.3558	0.6836	0.9224	0.1091	0.1744
SUB	1938	1.8129	**0.3391**	**0.6556**	0.9371	**0.1151**	**0.1873**

Table 4.1…continued

	N	Mean	P25	Median	P75	FRE0.15	FRE0.25
			P/R				
IND	2441	**1.3523**	0.4331	0.7420	0.9255	0.0709	0.1241
SUP	2421	1.7681	0.4039	0.6978	**0.9203**	0.0838	0.1417
SEC	2318	2.2917	**0.3876**	**0.6924**	0.9206	**0.0902**	**0.1544**
SUB	1884	2.8187	0.3905	0.7071	0.9395	0.0860	0.1423
			P/CgbO				
IND	2217	**1.0575**	0.3051	0.5639	0.8429	0.1141	0.2025
SUP	2201	1.3282	0.3010	0.5557	0.8597	0.1172	0.2099
SEC	2060	1.5485	0.2907	**0.5419**	**0.8395**	0.1136	0.2117
SUB	1685	1.2046	**0.2903**	0.5556	0.8811	**0.1282**	**0.2178**
			P/NCIfOA				
IND	2002	**1.4313**	0.3695	0.6904	**0.9227**	0.0904	0.1523
SUP	1987	2.0590	0.3628	0.6659	0.9228	0.1007	0.1676
SEC	1888	2.0587	0.3458	**0.6599**	0.9251	0.1065	0.1748
SUB	1459	2.1974	**0.2922**	0.6607	0.9440	**0.1076**	**0.1864**
			P/ NCIfIA				
IND	1144	**2.4148**	0.5210	0.8216	**0.9595**	0.0629	0.1119
SUP	1129	2.6679	0.4976	0.8100	0.9737	0.0735	0.1275
SEC	1042	14.8500	**0.4772**	**0.8016**	0.9787	0.0729	0.1238
SUB	759	4.4714	0.4774	0.8520	0.9985	**0.0856**	**0.1331**
			P/OD				
IND	1721	19.3454	0.3359	0.6466	0.9415	0.1023	0.1732
SUP	1700	46.5190	0.3286	0.6457	**0.9307**	0.1106	0.1859
SEC	1539	51.2018	0.2944	0.6290	0.9361	0.1209	0.2086
SUB	1202	**1.2065**	**0.2922**	**0.6004**	0.9698	**0.1348**	**0.2171**
			P/FCFE				
IND	1413	**1.8147**	0.4390	0.7638	**0.9438**	0.0807	0.1309
SUP	1401	1.9634	0.4178	0.7346	0.9563	**0.0878**	0.1363
SEC	1277	3.0326	0.3934	**0.7213**	0.9654	0.0838	**0.1464**
SUB	941	2.3423	**0.3376**	0.7432	0.9833	0.0786	0.1456
			P/FCFF				
IND	1586	**1.3765**	0.3587	0.6796	**0.9071**	0.0939	0.1658
SUP	1574	1.4325	0.3640	0.6860	0.9219	0.1061	0.1798
SEC	1427	1.5482	0.3485	**0.6632**	0.9237	0.1044	0.1843
SUB	1053	1.7767	**0.3333**	0.6980	0.9556	**0.1083**	**0.1909**

IND - Industry; SUP - Supersector; SEC - Sector; SUB - Subsector; N - Number of observations; P25 - 25th Percentile; P75 - 75th Percentile; FRE 0.15 - 15% FRE range; FRE 0.25 - 25% FRE range; P - Market Price per share; GP - Gross profit; EBITDA - Earnings Before Interest, Tax, Depreciation and Amortisation; EBIT - Earnings Before Interest and Tax; PAT - Profit After Tax; PBT - Profit Before Tax; HE - Headline Earnings; TA - Total Assets; IC - Invested Capital; BVE - Book Value of Equity; R - Revenue; CgbO - Cash generated by Operations; NCIfOA - Net Cash Inflow from Operating Activities; NCIfIA - Net Cash Inflow from Investment Activities; OD - Ordinary Dividends; FCFE - Free Cash Flow to Equity; FCFF - Free Cash Flow to the Firm; Highlighted figures - Optimal industry classification

The boxplots in Figure 4.3 illustrate that the data points are not normally distributed, but positively skewed; i.e. all 16 boxes are located significantly closer to the end of the bottom whiskers. This is the primary reason that researchers generally attach less value to the mean (Bhojraj & Lee, 2002; Liu *et al.,* 2002b; Beatty *et al.,* 1999). Therefore, although the mean is shown in the analysis, its inconsistent results over industry narrowing can be traced to its sensitivity to outliers and a declining sample size, as opposed to a measure of central tendency, such as the median, for example.

An interesting phenomenon depicted by the boxplots in Figure 4.4 is that the lower boundary of the box (P25) and the upper boundary of the box (P75) generally divert, which suggests that the more accurate valuations prior to industry narrowing became even more accurate with industry narrowing, and, *vice versa;* i.e. the less accurate valuations prior to industry narrowing became even less accurate with industry narrowing. On average, 81% of the variables tested demonstrated this tendency over the four industry classifications. This is evident from the widening IQRs in the boxplots in Figure 4.4. The median of the upper 50% of observations increased, therefore, as the industry classification was narrowed, while the median of the bottom 50% of observations decreased. Similarly, the median of the total population of observations also decreased as the industry classification was narrowed.

4.5.3   The impact of industry classification on valuation accuracy

The medians and FREs of the 64 pools of valuation errors all rendered similar results. As is evident from Table 4.1 and the 16 boxplots in Figure 4.4, industry narrowing does increase valuation accuracy, since the medians decrease and the FREs increase at some stage as the industry classification is narrowed. However, the boxplot notches in Figure 4.4 indicate that not all the multiples offered statistically significant improvements of the median at the 95% confidence level, over all the industry classifications. When the industry classification was narrowed from IND to SUP, only three multiples offered improvements of statistical significance, namely, EBITDA, EBIT and R. The number of multiples that offered statistically significant improvements at the 95% confidence level increased to eight when the industry
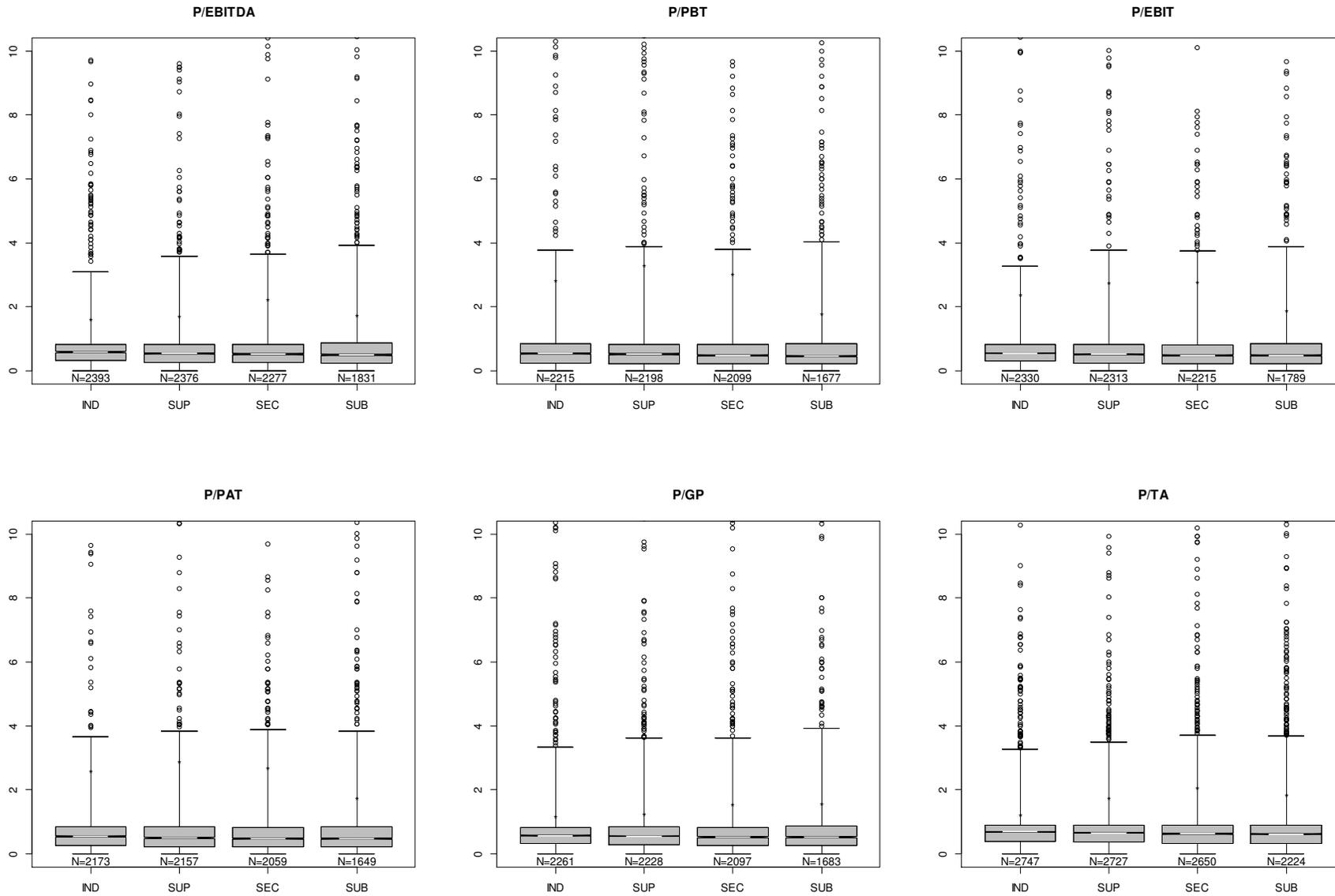
Figure 4.3: Valuation accuracy of multiples: Descriptive statistics (complete range)
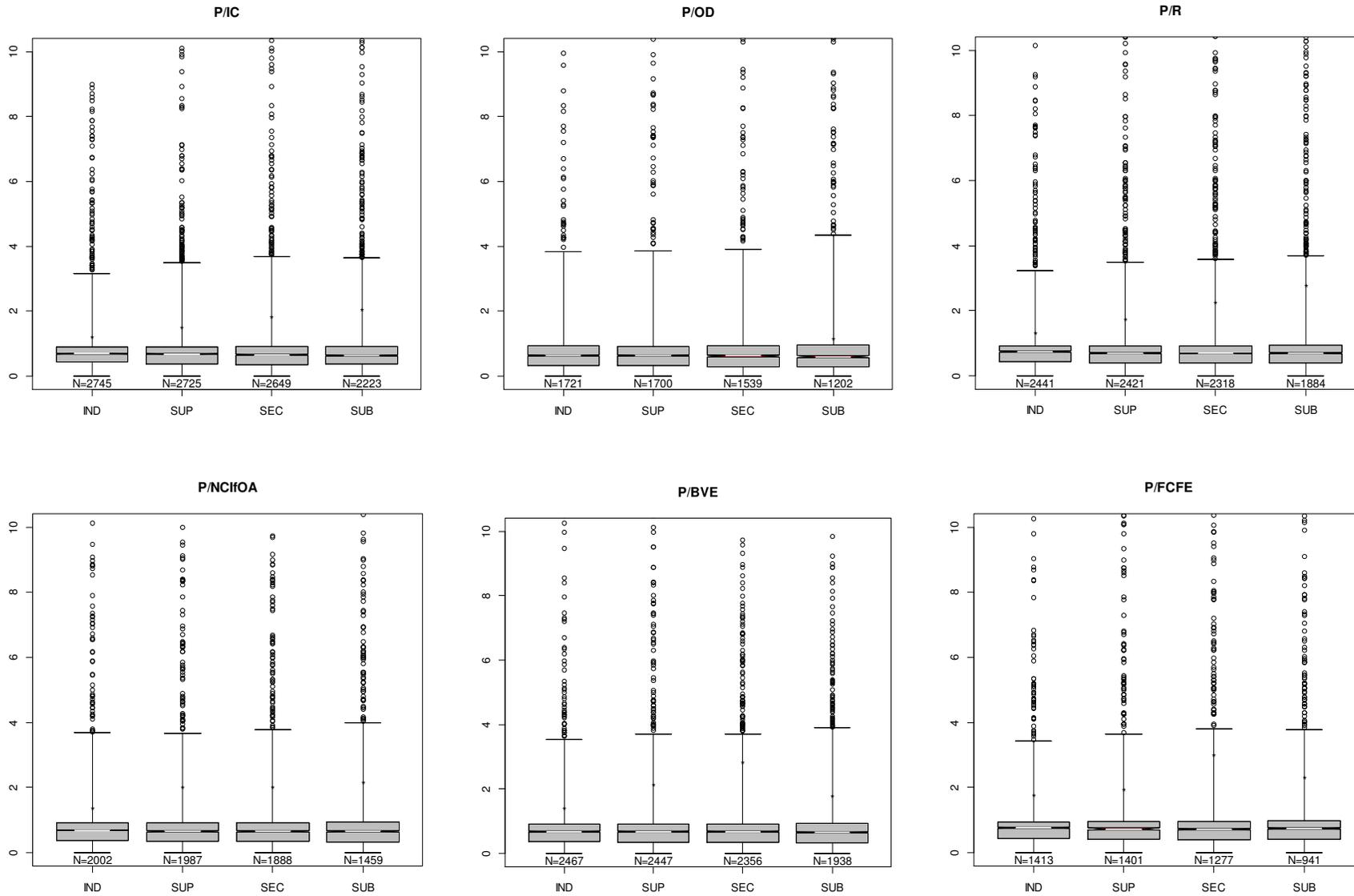
Figure 4.3…continued
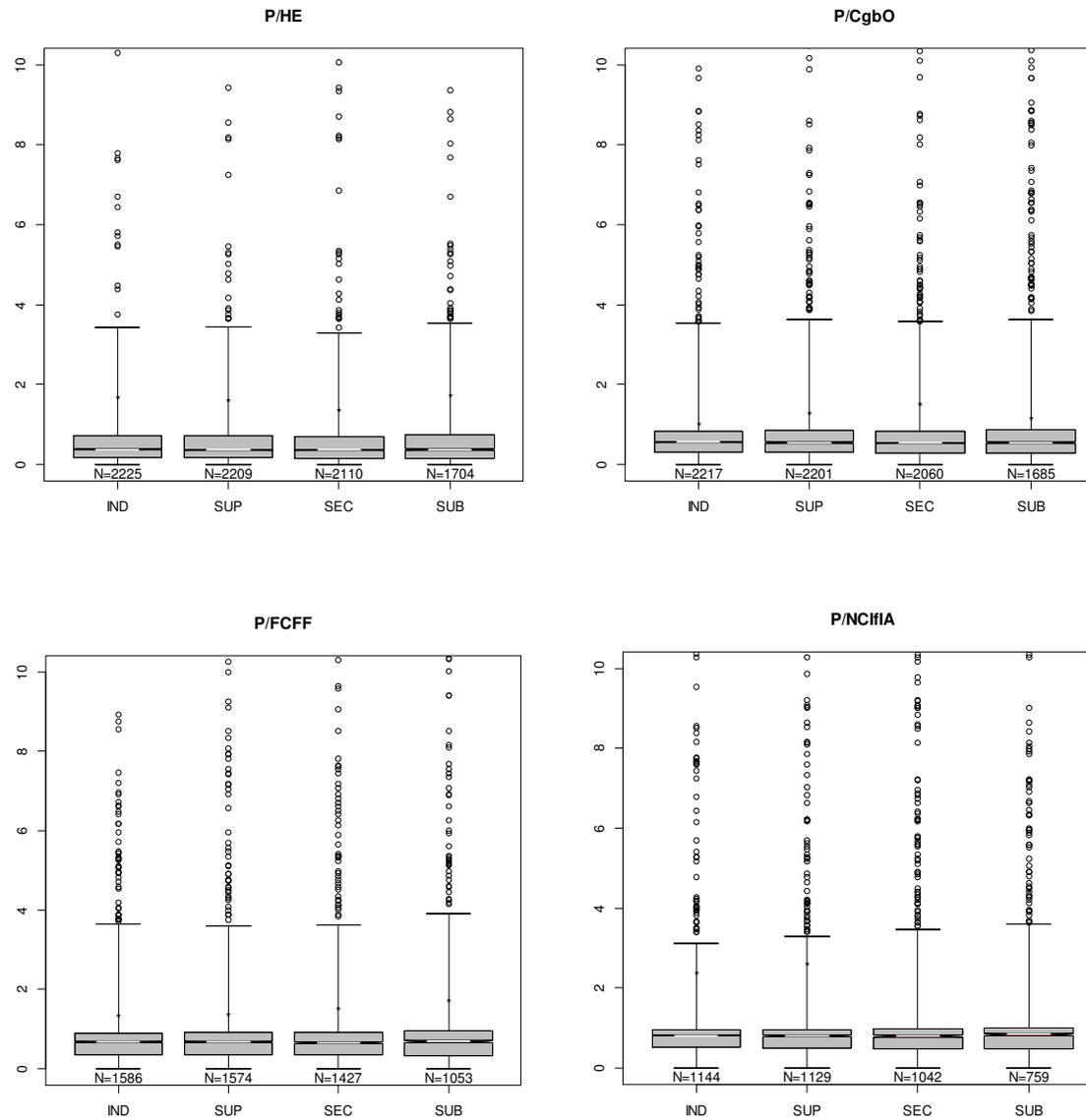
Figure 4.3…continued
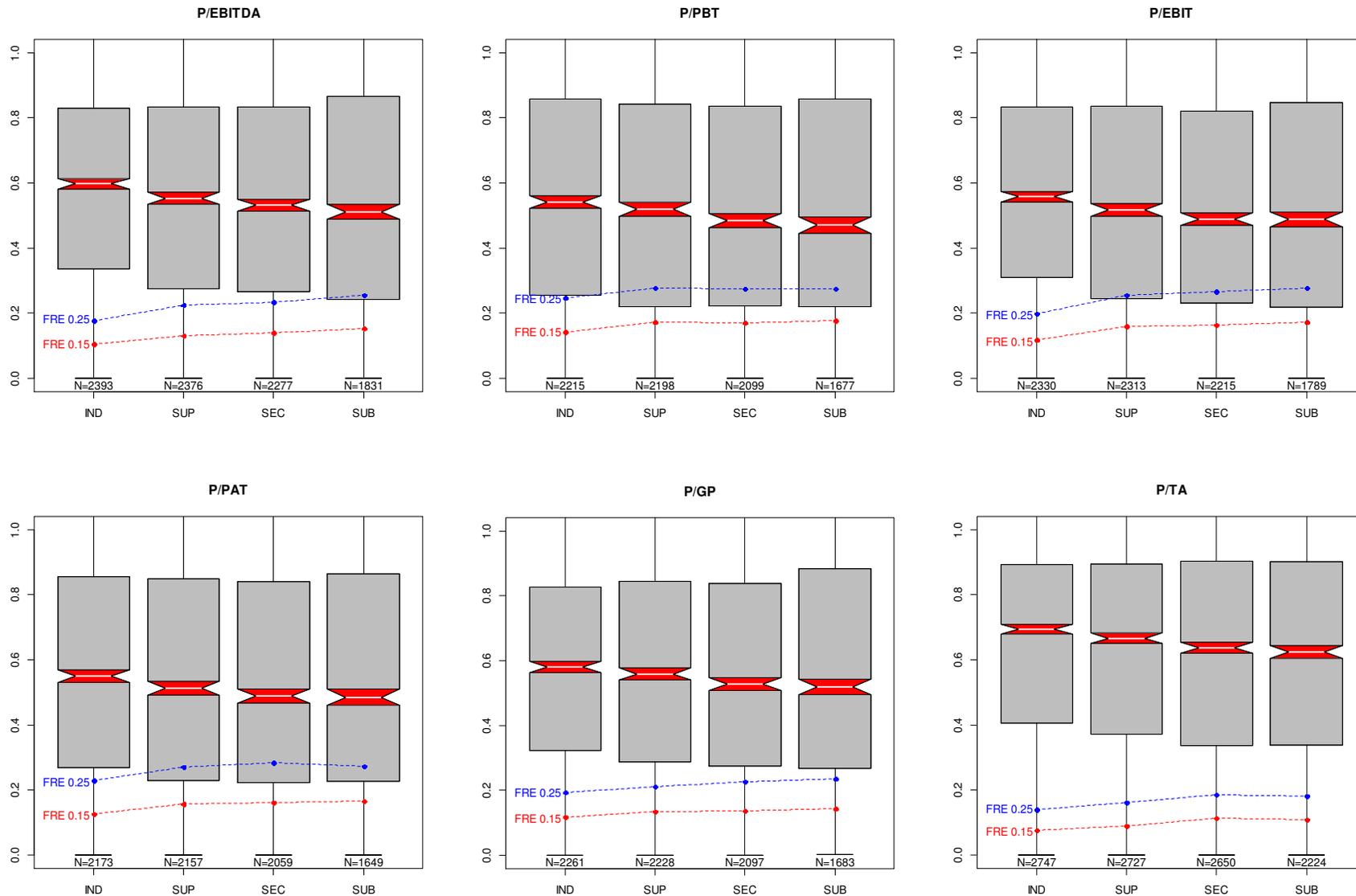
Figure 4.4: Valuation accuracy of multiples: Absolute median valuation errors and FREs (limited range focusing on the central 50% of the observations, i.e. the boxes)
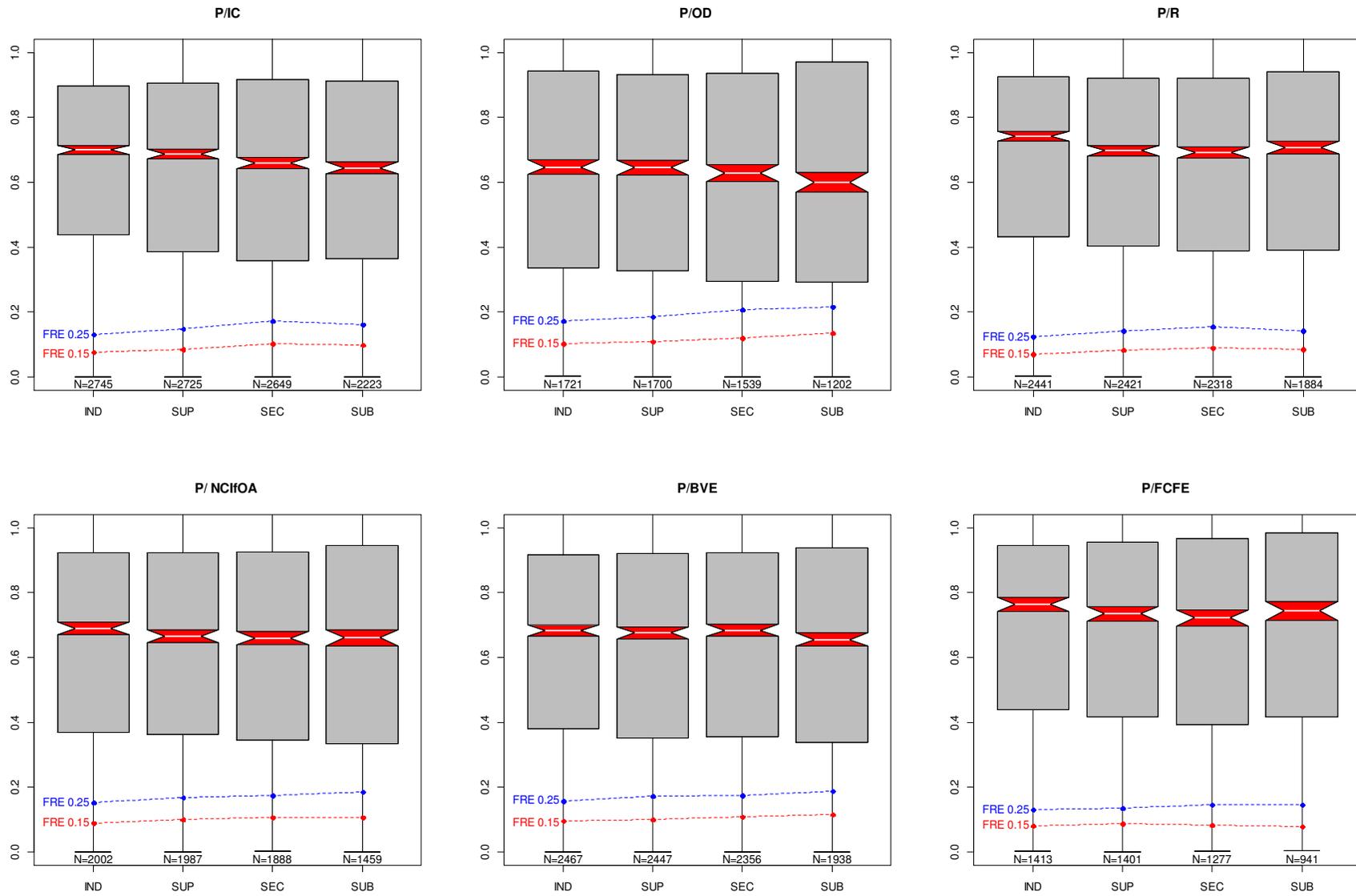
Figure 4.4…continued
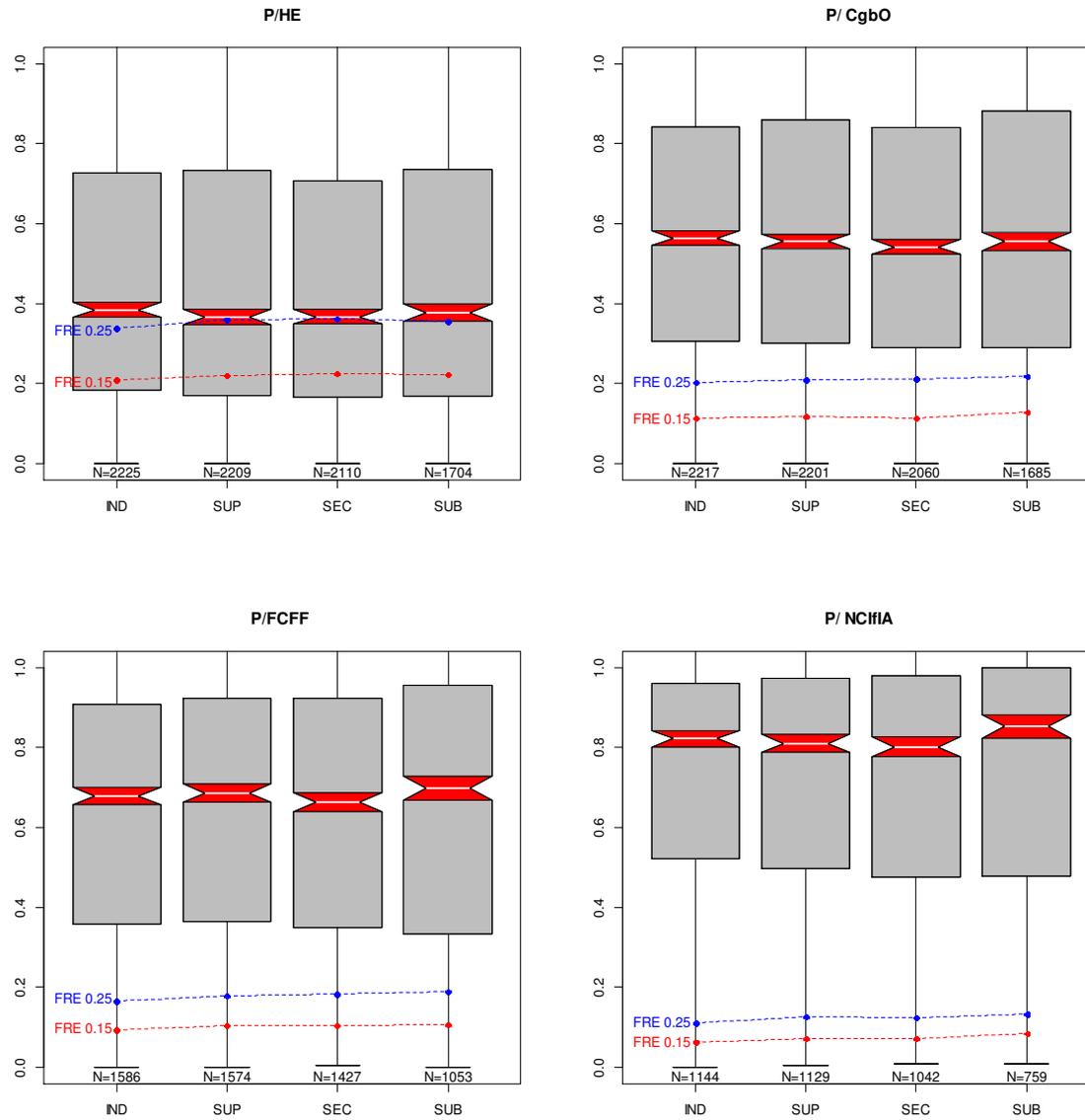
Figure 4.4…continued

classification was narrowed from IND to SEC. The eight multiples concerned were EBITDA, PBT, EBIT, PAT, GP, TA, IC and R. These eight multiples also offered statistically significant improvements at the 95% confidence level when the industry classification was narrowed further from IND to SUB.

In order to quantify the potential increase in valuation accuracy that industry narrowing could offer, an IVC was created in Table 4.2. Positive percentages in the IVC indicate, for each of the 16 multiples, to what extent the valuation accuracy of specific multiples increased when the industry classification was narrowed from one level to the next; i.e. from IND to SUP, from SUP to SEC and from SEC to SUB. Negative percentages indicate the opposite; i.e. to what extent the valuation accuracy of specific multiples decreased when the industry classification was narrowed. The highlighted percentages indicate the optimal industry classification for each multiple. The IMP between the widest (IND) and narrowest (SUB) industry classification is indicated in the last column in the IVC (IMP.IVC). The histograms below the various industry classification columns indicate the percentage of multiples that experienced an increase in valuation accuracy when the industry classification was consecutively narrowed from IND to SUP, SUP to SEC and SEC to SUB.

The incremental percentage increases, on average, in the median absolute valuation errors; i.e. the increase in valuation accuracy over all 16 multiples, when narrowing the industry classification from IND to SUP, SUP to SEC and SEC to SUB, were 3.50%, 2.90% and -0.001%, respectively. As is evident from these percentages, the magnitude of the increase in valuation accuracy declined as the industry classification was narrowed. This is in line with evidence from developed capital markets (Alford, 1992). The average increase in valuation accuracy over all 16 multiples when narrowing the industry classification from IND to SUP to SEC was 6.40%. However, when narrowing the industry classification further from SEC to SUB the average change in valuation accuracy over all 16 value driver categories was negligible (-0.001%). The latter also concurs with evidence from the developed market literature (Alford, 1992). Therefore, the overall results suggest that, on average, the SEC classification is the optimal industry classification. However, this may not be the case when each individual multiple is considered in isolation. The valuation accuracy of EBITDA, for example, increased by 3.78% when the industry

Table 4.2: Industry Value Chain: Absolute median valuation error and FRE 0.25 range

Median				Value drivers	FRE 0.25			
SUP	SEC	SUB	IMP.IVC		SUP	SEC	SUB	IMP.IVC
3.65%	5.58%	**1.44%**	10.68%	GP	8.80%	6.49%	**4.42%**	19.70%
7.44%	3.80%	**3.78%**	15.02%	EBITDA	26.80%	3.37%	**10.01%**	40.19%
7.14%	5.69%	**0.10%**	12.93%	EBIT	29.05%	3.75%	**4.63%**	37.43%
6.75%	4.62%	**0.76%**	12.13%	PAT	18.19%	**1.70%**	-0.29%	19.60%
3.99%	6.74%	**2.87%**	13.60%	PBT	**12.71%**	-0.93%	-0.11%	11.67%
4.80%	-0.22%	-2.56%	2.03%	HE	6.47%	**0.75%**	-1.71%	5.51%
3.98%	4.46%	**1.93%**	10.37%	TA	15.59%	**14.78%**	-3.00%	27.36%
1.80%	3.99%	**2.36%**	8.15%	IC	13.38%	**16.32%**	-6.38%	23.32%
1.13%	-1.18%	**4.10%**	4.04%	BVE	9.59%	0.40%	**7.40%**	17.39%
5.96%	**0.77%**	-2.12%	4.61%	R	14.18%	**8.96%**	-7.84%	15.31%
1.45%	**2.48%**	-2.53%	1.41%	CgbO	3.65%	0.86%	**2.88%**	7.39%
3.55%	**0.90%**	-0.12%	4.33%	NCIfOA	10.05%	4.30%	**6.64%**	20.98%
1.41%	**1.04%**	-6.29%	-3.84%	NCIfIA	13.94%	-2.90%	**7.51%**	18.55%
0.14%	2.59%	**4.55%**	7.27%	OD	7.33%	12.21%	**4.07%**	23.62%
3.82%	**1.81%**	-3.04%	2.60%	FCFE	4.13%	**7.41%**	-0.55%	10.99%
-0.94%	**3.32%**	-5.25%	-2.87%	FCFF	8.44%	2.50%	**3.58%**	14.53%
3.50%	2.90%	0.00%	6.40%	Average	12.64%	5.00%	1.96%	19.60%
3.50%	6.40%	6.40%		Cumulative	12.64%	17.64%	19.60%	

classification was narrowed further from SEC to SUB.

The median-based results concur with evidence from the developed capital markets. However, the developed market literature suggests a slightly higher overall increase in valuation accuracy. Schreiner (2007) tested the market in the USA and found that, when narrowing the industry classification from IND to SUP, the valuation accuracy of multiples increased by 4.49%, compared to an increase of 3.50% in the South African market.[23] Similarly, when narrowing the industry classification from SUP to SEC, the valuation accuracy increased by 5.85%, which is also higher than South Africa's 2.90%.

An overall increase in valuation accuracy when the industry classification was narrowed from IND to SUB was observed in 88% of the multiples. The exceptions were NCIfIA (3.84% decrease) and FCFF (2.87% decrease). An increase in valuation accuracy was observed for 94% of the multiples when the industry classification was narrowed from IND to SUP. The only exception was FCFF, which indicated a 0.94% decrease in valuation accuracy. The percentage of multiples that reflected an increase in valuation accuracy when the industry classification was narrowed from SUP to SEC was 88%. The two multiples that did not reflect an increase in valuation accuracy were HE (0.22% decrease) and BVE (1.18% decrease).

However, when narrowing the industry classification from SEC to SUB, the percentage of multiples that reflected an increase in valuation accuracy declined substantially to 56%. The seven multiples that failed to reflect an increase in valuation accuracy were HE (2.56% decrease), R (2.12% decrease), CgbO (2.53%

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[23] Schreiner's initial analysis included the valuation performance of forward and knowledge-related multiples. However, for the purpose of comparison, the median-based overall valuation performance indicates an average IMP of 4.49% and 5.85%, which is presented after the omission of forward and knowledge-related multiples from their initial analysis. Forward multiples were omitted since comparative forward multiples are not readily available on South African databases. Knowledge-related multiples, on the other hand, are nonsensical in the South African context as a result of accounting differences between South African and American Generally Accepted Accounting Practice (GAAP). Similarly, the FRE-based IMPs are 8.42% and 8.85%.

decrease), NCIfOA (0.12% decrease), NCIfIA (6.29% decrease), FCFE (3.04% decrease) and FCFF (5.25% decrease).

The top five individual multiples, which experienced the most significant increase in valuation accuracy when the industry classification was narrowed from IND through to SUB, were EBITDA (15.02%), PBT (13.60%), EBIT (12.93%), PAT (12.13%) and GP (10.68%).

The analysis of the FREs 0.15 and 0.25 rendered similar results. The proportion of valuation errors in the 25% error range increased, on average, over all 16 multiples, when the industry classification was narrowed from IND to SUP, SUP to SEC and SEC to SUB. The percentage increases offered within the FRE 0.25 range were 12.64%, 5.00% and 1.96%, respectively. As with the median analysis, the magnitude of the increase in valuation accuracy declined as the industry classification was narrowed. The average increase in valuation accuracy over all 16 multiples, when narrowing the industry classification from IND to SUP to SEC to SUB, was 19.60%. Although not shown here, the 15% error range offered, on average, an even higher increase in valuation accuracy of 23.82%. The overall FRE-based results suggest that the SUB classification is the optimal industry classification. However, in the case of the median, this will not hold when each individual multiple is considered in isolation. The valuation accuracy of R, for example, decreased by 7.84% when the industry classification was narrowed from SEC to SUB.

The FRE-based results also concur with evidence from the developed market literature, which suggests an overall increase in valuation accuracy when narrowing the industry classification from IND to SUP of 8.42%, compared to South Africa's 12.64% (Schreiner, 2007). Similarly, when narrowing the industry classification from SUP to SEC evidence from the USA indicates an overall increase in valuation accuracy of 8.85%, compared to South Africa's 5.00%.

The fractional error analysis indicated an overall increase in valuation accuracy in 100% of the multiples when the industry classification was narrowed from IND to SUB. A step-wise industry refining approach revealed that 100% of the multiples indicated an increase in valuation accuracy when the industry classification was

narrowed from IND to SUP. The percentage of multiples that reflected an increase in valuation accuracy when the industry classification was narrowed from SUP to SEC was 88%. The two multiples that failed to reflect an increase in valuation accuracy were PBT (0.93% decrease) and NCIfIA (2.90% decrease). However, as was the case with the median, when the industry classification was narrowed from SEC to SUB, the percentage of multiples that reflected an increase in valuation accuracy declined substantially to 56%. The seven multiples that did not reflect an increase in valuation accuracy were PAT (0.29% decrease), PBT (0.11% decrease), HE (1.71% decrease), TA (3.00% decrease), IC (6.38% decrease), R (7.84% decrease) and FCFE (0.55% decrease).

The top five individual multiples, which experienced the most substantial increase in valuation accuracy when the industry classification was narrowed from IND through to SUB, were EBITDA (40.19%), EBIT (37.43%), TA (27.36%), OD (23.62%) and IC (23.32%).

These findings offer empirical support in favour of peer group selection based on entities with similar industry classifications. Therefore, one can deduce that industry classification is a viable proxy for peer group selection purposes, i.e. industry classification successfully groups together homogeneous entities with similar risk and earnings growth characteristics.

4.6   CONCLUSION

The primary aim of Chapter 4 was to establish whether narrower industry classifications increase the valuation accuracy of multiples and, in so doing, to present an emerging market perspective in this regard. The research results presented strong evidence in support of the use of narrower industry classifications when employing multiples to perform equity valuations and consequently verified H1. The absolute median valuation error and FRE 0.25 indicated an overall increase in valuation accuracy when the industry classification was narrowed from IND to SUB for 88% and 100% of the multiples, respectively. The corresponding percentages when the industry classification was narrowed from IND to SUP, were 94% and

100% of the multiples, respectively. These improvements in valuation accuracy declined to 88% of the multiples when the industry classification was narrowed from SUP to SEC and to 56% of the multiples when the industry classification was narrowed from SEC to SUB. It is therefore evident that narrower industry classifications explain market values more accurately than wider industry classifications, which is in line with empirical evidence from developed markets.

The secondary aim was to determine the potential improvement in valuation accuracy that industry narrowing may offer *vis-à-vis* wider industry classifications. Based on the absolute median valuation errors and FREs 0.25, the overall average IMP.IVC in valuation accuracy by employing narrower industry classifications lies between 6.40% and 19.60%. Individual multiples, however, demonstrated more substantial results. The P/EBITDA multiple, for example, indicated an improvement of 15.02% in the absolute median valuation error and 40.19% in the 25% error range. It is therefore evident that narrower industry classifications do improve valuation accuracy, but with varying degrees.

The third aim was to determine the optimal industry classification for peer group selection purposes. The research results indicated that, on average, narrowing the industry classification beyond that of SEC added little, if any, value. This concurs with evidence from developed capital markets, which indicates that narrowing industry classifications beyond 3-digit codes adds little value. However, the evidence does suggest that multiples have different optimal industry classifications and that, when individual multiples are considered in isolation, there may be value in narrowing the industry classification further to SUB, as was the case with the P/EBITDA multiple, for example.

The evidence therefore suggests that investment practitioners in the South African market should consider employing the narrowest industry classification possible when constructing a peer group multiple. A narrower industry classification could provide an increase in valuation accuracy of up to 19.60%, on average, which offers a substantial improvement over wider industry classifications. The potential increase in valuation accuracy when consideration is given to individual multiples is even greater. The P/EBITDA multiple, for example, offers a potential increase in valuation

accuracy of between 15.02% and 40.19% as the industry classification is narrowed from IND to SUB.

Although one may be inclined to pursue other, more diligent approaches to peer group selection, which may enhance the valuation accuracy of these multiples further, the focus of Chapter 4 was on the specific contribution that a narrower industry classification may offer in this regard. The further enhancement of peer group selection strategies, based on valuation fundamentals as opposed to industry classifications, is investigated in Chapter 5.

CHAPTER 5

THE IMPACT OF VALUATION FUNDAMENTALS-BASED PEER GROUP SELECTION ON THE VALUATION ACCURACY OF MULTIPLES

5.1   INTRODUCTION

As was the case with Chapter 4, the focus of Chapter 5 is on the peer group selection process. The research results in Chapter 4 indicated that multiples whose peer groups were based on narrower industry classifications produced more accurate valuations compared to multiples whose peer groups were based on wider industry classifications. However, there may be alternative, perhaps more diligent, approaches to peer group selection. One such alternative is peer group selection based on valuation fundamentals, which is the focus of Chapter 5.

The objective is to test the impact that peer group selection based on a careful selection of valuation fundamentals might have on the valuation accuracy of multiples. A careful selection of valuation fundamentals implies that not all valuation fundamentals are created equally. Indeed, the premise of the research conducted in Chapter 5 is that a combination of two or more valuation fundamentals will more closely align entities with similar growth and risk characteristics. Consequently, H2 postulates the following:

H2:   Multiples whose peer group selection is based on a combination of valuation fundamentals, i.e. smaller groups of more homogeneous entities, offer higher degrees of valuation accuracy *vis-á-vis* multiples whose peer group selection is based on single valuation fundamentals, i.e. larger groups of more heterogeneous entities.

As was the case with H1, there is no empirical evidence in support of this phenomenon in the emerging market literature. In a similar vein, there is no theoretical guidance in South Africa regarding which, if any, valuation fundamentals

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should be combined, and how this should be accomplished for peer group selection purposes.

Similarly, assuming that a peer group selection strategy based on a combination of valuation fundamentals will outperform a strategy based on single valuation fundamentals, may produce *a priori* theoretical solutions with little, if any, capacity for practical application. As the evidence will show, the latter is of particular concern in emerging markets, such as South Africa, where the capital markets have limited depth and breadth.

Secondly, as in the case of Chapter 4, one should also consider whether it is meaningful to combine valuation fundamentals, i.e. does it result in a material increase in valuation accuracy? Consequently, it is equally important to consider the magnitude of an increase in valuation accuracy that a combination of valuation fundamentals may offer.

The third aim is to establish which valuation fundamentals, if any, offer the greatest degree of explanatory power. The fourth aim is to compare the valuation performance of multiples whose peer groups are based on industry classifications with multiples whose peer groups are based on valuation fundamentals. It is envisaged that the investigation in Chapter 5 will offer empirical guidance in this respect.

5.2   LITERATURE REVIEW

The premise of the valuation fundamentalists is that peer group selection should be based on entities with similar valuation fundamentals, i.e. variables such as profitability, growth and risk (Dittmann & Weiner, 2005; Goedhart *et al.*, 2005). For example, in order to compile a peer group, the target entity's TA, expected earnings growth or RoE is used as a benchmark variable to identify other entities with similar valuation fundamentals (Damodaran, 2006b).

Most existing literature regarding peer group selection methodology hinges on the principle work by Alford (1992), who investigated the efficacy of peer group selection in the USA market in 1978, 1982 and 1986. Apart from testing the valuation accuracy of multiples whose peer groups were based on various industry classifications, Alford also tested the impact of two valuation fundamentals. He controlled for risk, via entity size, and earnings growth, via RoE, and found that these valuation fundamentals had little effect on valuation accuracy.

In an extension of Alford's work, Bhojraj and Lee (2002) argue for the selection of a peer group on the basis of similar valuation fundamentals instead of industry classification. Bhojraj and Lee (2002) used regression analysis to develop a "warranted multiple" for the target entity, which was subsequently used to identify the target entity's peer group, i.e. those entities with the closest multiple to the target entity's "warranted multiple". The harmonic mean of the peer group was then used to calculate the value of the target entity. Bhojraj and Lee's research results indicate that multiples whose peer groups are selected in this manner offer substantial improvements in valuation performance over multiples whose peer groups are selected on the basis of industry or size, for example.

Also based on Alford's work, Dittmann and Weiner (2005) obtained similar research results when they tested peer group selection methods in various countries in the European Union. Dittmann and Weiner (2005) conducted a study on a sample of European and USA entities in 16 countries over the 10-year period from 1993 to 2002 to determine the most accurate method for selecting a peer group. Their results confirmed that the selection of a peer group based on valuation fundamentals, specifically Return on Assets (RoA) or a combination of RoA and TA, offers superior results *vis-à-vis* the conventional industry partitioning approach. The most accurate selection criterion for the USA, the UK and Ireland was a combination of RoA and TA. However, for the remaining 13 countries, valuation accuracy did not improve significantly when adding TA as an additional control factor, indicating that, for these 13 countries, TA bore only marginal incremental information content beyond RoA.

In a similar vein, Cheng and McNamara (2000) tested the valuation accuracy of the P/EPS and P/BVE multiples and concluded that industry classification and RoE are

the most effective selection criteria. Similarly, Goedhart *et al.* (2005) concluded that peer group selection should be based on similar returns on invested capital and growth rates. In keeping with this research, Henschke & Homburg (2009) concluded that the use of financial ratios, coupled with adjustments to multiples for additional differences, yields the most accurate valuations. They found that, when controlling for differences in financial ratios, industry classification is not a crucial criterion for selecting a peer group.

Herrmann and Richter (2003) also present evidence that indicates a greater degree of valuation accuracy when employing peer group selection methods that are based on valuation fundamentals. They controlled for growth, profitability and risk; and their research results strongly support the control of relevant variables rather than industry classification. Herrmann and Richter (2003) investigated peer group selection based on valuation fundamentals and industry partitioning for a sample of USA and European entities for the three years 1997, 1998 and 1999. They employed a recombining binomial model, coupled with a risk-neutral valuation approach, to test the valuation accuracy of various control factors, which they compared to the more conventional industry classification system. Their results indicated that, when controlling for the factors earnings growth and RoE across the market, i.e. with no industry partitioning, the valuation accuracy improves *vis-à-vis* the more conventional industry partitioning approach. The improvement in valuation accuracy becomes even more significant when substituting historical earnings growth with investment practitioners' long-term growth forecasts. Interestingly, Herrmann and Richter found that the valuation accuracy does not improve significantly when combining conventional industry partitioning with these control factors, indicating that industry classification does not carry incremental information content beyond long-term earnings growth and RoE.

International evidence therefore suggests that peer group selection based on valuation fundamentals offers superior explanatory power *vis-à-vis* peer group selection based on industry classification. However, the existing empirical evidence is based on the relatively deep and liquid trading markets in developed regions in the USA and Europe. Empirical evidence focusing on the new investment frontiers such as the BRICS countries is limited. The only empirical findings on peer group

selection methodology in South Africa is offered by Nel *et al.* (2013a), who found that multiples whose peer groups were based on narrower industry classifications produced more accurate valuations compared to multiples whose peer groups were based on wider industry classifications. No empirical findings on peer group selection based on valuation fundamentals have yet been documented in South Africa. Therefore, the research conducted in Chapter 5 aims to offer an emerging market perspective in this regard.

5.3   DATA SELECTION

The number of observations differed for each multiple and valuation fundamental, or combination of valuation fundamentals, depending on how well the multiples satisfied the criteria stipulated in Section 3.2. As a result, the multiples have different population sizes for different valuation fundamentals or combinations thereof, varying between 433 and 2 656 observations. The total population of multiples included 172 318 observations, which were used to calculate 16 multiples, i.e. multiples where P was used as the MPV.

5.4   RESEARCH METHODOLOGY

As previously, the aim is to establish the ability of valuations based on Equation (3.1) to approximate actual share values. The peer group selection methodology presented in Chapter 3 is adjusted to accommodate the validation of H2. To this end, the target entity's peer groups are based on three fundamental variables, namely profitability, growth and risk. Three proxies that are commonly used in international literature for these three fundamental variables are RoE, Rg and TA (Henschke & Homburg, 2009; Damodaran, 2006b; Dittmann & Weiner, 2005; Herrmann & Richter, 2003; Cheng & McNamara, 2000; Alford, 1992). While RoE and Rg are considered to be good proxies for profitability and growth, TA is frequently considered as a proxy

for risk, since smaller entities are considered to be riskier than larger entities.[24] The choice of these three proxies affords one the opportunity to compare developed market findings with those of emerging markets. The three proxies are used individually and in combination, culminating in seven peer group selection criteria. Three of the seven criteria were single valuation fundamentals, namely RoE, Rg and TA; and four were combinations of these three valuation fundamentals, namely RoE.TA, RoE.Rg, TA.Rg and RoE.TA.Rg. These seven criteria were used to create peer groups for the construction of the 16 multiples contained in Table 2.1.

For the purpose of Chapter 5, peer groups are formed based on the value of the target entity's valuation fundamental, i.e. the benchmark valuation fundamental. All entities, across the market, whose valuation fundamentals fall within a certain deviation, say 30%, from the value of the benchmark valuation fundamental, are included in the peer group. For example, if target entity A has an RoE of 10%, its peer group will consist of all entities in the market with an RoE of between 7% and 13%. Although applying a deviation margin of 30% may seem arbitrary, the results were also compared for a 20% and 40% deviation margin. The median, in particular, showed an insubstantial change for these adjusted levels, while the number of entities changed substantially in the process. Consequently, the results reported on are based on a deviation margin of 30%, since it produced reasonably sized comparable entity sets, while still acting as a filter for entities with similar valuation fundamentals.

Each entity's multiple estimate ($\hat{\lambda}_{pt}^{e}$) is determined out-of-sample and is multiple-specific. The $\hat{\lambda}_{pt}^{e}$ is calculated as the harmonic mean of the multiples of all the entities included in the target entity's peer group, excluding that of the target entity.

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[24] Note that an accounting ratio analysis is a valuable tool in the dissemination of differences in operational and financial characteristics between the target entity and the entities that comprise the peer group. As such, accounting ratio analysis could prove particularly helpful when considering *ex post* model adjustments. However, the focus in this dissertation is on an *ex ante* model construction in particular. Consequently, accounting ratio analysis was not addressed in greater detail than that which is presented in Chapter 2 and the use of the three proxies included in Chapter 5.

Thereafter, the analysis follows the same generic approach as set out in Section 3.4.1, i.e. Equations (3.1) to (3.3) are applied to eventually arrive at the standardised form of (3.3), where ε_{it} is expressed proportionally to V_{it}^{e} in Equation (3.4):

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

The *R function CalcVEVds.peergroup* was written to implement Equation (3.4). The output of *CalcVEVds.peergroup* contained 112 pools of valuation errors (ε_{it}), i.e. seven different pools of valuation errors for each of the 16 multiples. These ε_{it} were analysed with the use of the *R function AnalyseVE.Fund*. Each pool of valuation errors was therefore multiple-specific and based on one of the seven criteria. This affords one the opportunity to assess the relative valuation performance of each multiple, of which the peer group was based on three different single valuation fundamentals or combinations thereof.

The valuation performance of the fundamentals-based multiples is evaluated by comparing the central tendency and dispersion of their respective valuation errors. The superior valuation fundamental, i.e. the valuation fundamental that produces the most accurate equity valuation, will typically be the one with the lowest summarised valuation error. In order to assess the relative valuation performance of the valuation fundamentals, an opportunity cost table was created, which indicates the extent to which the valuation accuracy of multiples improved, depending on the choice, or combination, of valuation fundamentals. The opportunity cost table indicates the IMP in valuation accuracy that may be secured by employing the optimal valuation fundamental (a valuation fundamental that has the smallest ε_{it}) or, combination of valuation fundamentals, rather than any of the suboptimal choices (a valuation fundamental that does not have the smallest ε_{it}).

5.5 EMPIRICAL RESULTS

The valuation performance of the 16 multiples was compared in order to ascertain which multiples offered the most accurate valuations. In total, 96 pools of valuation errors, based on six of the seven criteria, were estimated. Note that a combination of all three single valuation fundamentals, namely RoE.TA.Rg, was also tested, but due to the limited depth of the South African market, the number of peer groups produced by this combination was negligible. Consequently, the combination RoE.TA.Rg was excluded from this analysis.

This section explored the central tendency and dispersion of the valuation errors of the selected 16 multiples. This affords one the opportunity to assess the valuation performance of the multiples based on the choice of valuation fundamentals. First, the central tendency of each of the six pools of valuation errors was compared in order to ascertain, for each multiple, which pool contained the smallest cluster of absolute valuation errors. The measures of central tendency that were initially used to analyse the pools of valuation errors were the mean and the median. Second, the dispersion of the pools of valuation errors around the mean and the median was analysed using five measures of dispersion, namely the SD, CV, IQR, MAD and the CMAD. For each multiple, the variation within each of the six pools of valuation errors was compared in order to determine which valuation fundamental resulted in the narrowest dispersion of data. These measures are contained in Table 5.1.

5.5.1 Central tendency of the data

As is evident from Table 5.1 and the boxplots in Figures 5.1 and 5.2, the number of entity year observations (N) declined substantially when the peer group selection was based on a combination of valuation fundamentals, rather than on a single valuation fundamental. Although the outliers were rather prevalent with the single valuation fundamentals, they abated somewhat when the peer group selection was based on a combination of valuation fundamentals.

Table 5.1: Summary of absolute valuation errors over six valuation fundamentals

Fundamental	N	Mean	Median	SD	CV	IQR	MAD	CMAD
P/GP								
RoE	2 176	1.3211	0.6496	7.3147	5.5367	0.5127	0.3808	0.5862
TA	2 415	1.4467	0.6548	9.1806	6.3457	0.4960	0.3689	0.5633
Rg	1 963	1.5806	0.6638	10.6010	6.7070	0.4888	0.3586	**0.5403**
RoE.TA	716	**0.9774**	**0.5614**	**2.2311**	**2.2827**	0.4934	0.3666	0.6530
RoE.Rg	814	1.1132	0.5977	2.8583	2.5676	**0.4777**	**0.3496**	0.5849
TA.Rg	606	1.4155	0.6020	7.9200	5.5951	0.5079	0.3830	0.6362
P/EBITDA								
RoE	2 395	1.2969	0.5275	7.4521	5.7459	0.5456	0.3947	0.7482
TA	2 634	1.7266	0.5731	16.6867	9.6648	0.5408	0.3884	**0.6778**
Rg	1 989	1.6171	0.5335	12.1401	7.5072	0.5252	0.3807	0.7136
RoE.TA	777	**0.6730**	0.4015	**1.3792**	**2.0494**	0.4716	0.3228	0.8039
RoE.Rg	815	0.7991	**0.3911**	2.6364	3.2993	**0.4387**	**0.3216**	0.8222
TA.Rg	603	0.7696	0.4244	1.8266	2.3735	0.5007	0.3454	0.8140
P/EBIT								
RoE	2 370	1.2836	0.5125	5.5359	4.3129	0.5448	0.3939	**0.7687**
TA	2 620	1.8381	0.5446	19.2495	10.4727	0.6227	0.4198	0.7708
Rg	1 979	1.7691	0.4987	15.2952	8.6457	0.5967	0.3956	0.7932
RoE.TA	775	**0.6565**	0.3821	**1.2836**	**1.9551**	0.4440	0.3059	0.8005
RoE.Rg	812	0.7526	**0.3688**	2.5751	3.4217	**0.4035**	**0.2903**	0.7872
TA.Rg	601	0.8521	0.4020	2.4398	2.8633	0.5141	0.3410	0.8483
P/PAT								
RoE	2 310	1.6637	0.4860	9.6668	5.8104	0.6037	0.4075	0.8385
TA	2 619	2.5303	0.5717	24.2577	9.5869	0.7406	0.5075	0.8877
Rg	1 965	2.5262	0.5306	19.6997	7.7981	0.7025	0.4411	**0.8313**
RoE.TA	766	**0.6499**	0.3750	**1.2539**	**1.9294**	0.4712	0.3238	0.8634
RoE.Rg	809	0.7555	**0.3688**	2.0910	2.7679	**0.4330**	**0.3183**	0.8631
TA.Rg	586	1.2089	0.4520	3.9918	3.3021	0.6250	0.4010	0.8873
P/PBT								
RoE	2 306	1.5035	0.4581	7.5852	5.0449	0.5839	0.3872	**0.8452**
TA	2 619	2.2902	0.5320	25.3628	11.0747	0.7310	0.4762	0.8951
Rg	1 965	2.1765	0.5131	17.9640	8.2538	0.6904	0.4520	0.8810
RoE.TA	767	**0.5930**	0.3382	**1.1107**	**1.8730**	0.4041	0.2924	0.8645
RoE.Rg	810	0.7496	**0.3323**	2.6618	3.5508	0.4122	0.2979	0.8963
TA.Rg	589	1.0656	0.4338	3.3069	3.1033	0.5869	0.3921	0.9040
P/HE								
RoE	2 325	1.6091	0.4028	12.3218	7.6578	0.5849	0.3736	0.9275
TA	2 601	1.5680	0.4237	13.2682	8.4618	0.7277	0.4224	0.9969
Rg	1 960	1.7092	0.4154	13.9263	8.1476	0.6529	0.3990	0.9606
RoE.TA	776	**0.4792**	0.2956	**1.0216**	**2.1319**	0.3787	0.2600	0.8796
RoE.Rg	810	0.5919	**0.2888**	2.0803	3.5146	0.3889	**0.2527**	0.8749
TA.Rg	589	0.9116	0.3565	3.4883	3.8264	0.4511	0.3059	**0.8580**
P/TA								
RoE	2 458	1.5784	0.6108	14.2423	9.0232	**0.4419**	**0.3236**	0.5297
TA	2 656	1.3615	0.6300	5.3724	3.9458	0.4781	0.3453	0.5481
Rg	1 993	1.3197	0.6274	5.1006	3.8650	0.4544	0.3309	**0.5274**
RoE.TA	788	0.7890	0.4844	**1.5446**	**1.9576**	0.4775	0.3546	0.7322
RoE.Rg	816	**0.7439**	**0.4716**	1.5684	2.1083	0.4708	0.3474	0.7367
TA.Rg	609	0.8849	0.5630	1.9821	2.2399	0.5238	0.3870	0.6873
P/IC								
RoE	2 462	1.5676	0.6246	14.1979	9.0568	**0.4522**	**0.3301**	**0.5285**
TA	2 655	1.3344	0.6508	4.9372	3.6998	0.4942	0.3569	0.5483
Rg	1 997	1.3325	0.6477	4.9329	3.7019	0.4637	0.3429	0.5295
RoE.TA	788	**0.8156**	0.5184	**1.5770**	**1.9335**	0.4948	0.3718	0.7173
RoE.Rg	816	0.8604	**0.4950**	2.5938	3.0148	0.4834	0.3609	0.7291
TA.Rg	611	0.9496	0.5830	2.1863	2.3024	0.5118	0.3776	0.6477

Table 5.1…continued

Fundamental	N	Mean	Median	SD	CV	IQR	MAD	CMAD
P/BVE								
RoE	2 418	1.2320	0.4888	8.3314	6.7626	0.5286	0.3858	0.7895
TA	2 637	1.4060	0.6495	8.7279	6.2076	0.5813	0.4319	0.6649
Rg	1 964	1.7224	0.6400	16.7496	9.7244	0.5700	0.4246	**0.6635**
RoE.TA	784	**0.5626**	0.3852	**0.9856**	**1.7519**	**0.4025**	0.2972	0.7714
RoE.Rg	809	0.6513	**0.3782**	1.6079	2.4689	0.4093	**0.2943**	0.7781
TA.Rg	589	1.0630	0.6246	2.6559	2.4985	0.6344	0.4614	0.7387
P/OD								
RoE	1 529	1.0295	0.5085	4.6591	4.5256	**0.5538**	**0.4033**	0.7931
TA	1 672	22.1383	0.5534	815.6295	36.8424	0.5667	0.4239	**0.7659**
Rg	1 341	17.7100	0.5175	614.2852	34.6858	0.5813	0.4162	0.8042
RoE.TA	553	0.7979	0.5012	1.3415	1.6813	0.5635	0.4102	0.8185
RoE.Rg	661	**0.7114**	**0.4446**	1.1552	1.6239	0.5683	0.4074	0.9164
TA.Rg	433	0.7547	0.5119	**1.0664**	**1.4129**	0.6372	0.4261	0.8324
P/CgbO								
RoE	2 369	1.5923	0.5918	10.1343	6.3645	0.6805	0.4807	0.8122
TA	2 615	1.7341	0.5919	13.1692	7.5943	0.6820	0.4729	0.7990
Rg	1 974	2.3132	0.5405	29.4159	12.7167	0.5913	0.4123	**0.7628**
RoE.TA	761	0.7615	0.4689	**1.4543**	**1.9098**	0.5641	0.4113	0.8771
RoE.Rg	807	**0.7151**	**0.4049**	1.6178	2.2624	0.4986	0.3585	0.8854
TA.Rg	596	0.9252	0.4461	4.1644	4.5009	**0.4964**	**0.3582**	0.8030
P/NCIfOA								
RoE	2 350	3.7232	0.7458	55.3889	14.8767	0.7664	0.5514	0.7394
TA	2 616	5.8618	0.7879	163.2479	27.8496	0.7449	0.5488	**0.6965**
Rg	1 964	35.5839	0.7342	1 449.9050	40.7460	0.7537	0.5332	0.7263
RoE.TA	737	**0.9765**	0.6343	**1.4339**	**1.4684**	0.6808	0.5066	0.7987
RoE.Rg	802	1.0615	**0.5679**	3.3546	3.1602	**0.6737**	**0.4791**	0.8436
TA.Rg	575	1.1584	0.6961	2.3413	2.0211	0.6947	0.5136	0.7378
P/NCIfIA								
RoE	2 178	2.8770	1.1020	12.0799	4.1988	**1.2476**	0.7939	0.7204
TA	2 577	4.6609	1.1825	54.0763	11.6021	1.4497	0.8740	0.7391
Rg	1 892	3.2887	1.1159	25.4478	7.7378	1.2946	**0.7664**	**0.6868**
RoE.TA	569	3.0438	1.0832	15.8030	5.1919	1.4374	0.8965	0.8277
RoE.Rg	755	**2.1905**	**1.0357**	**5.7578**	**2.6285**	1.3458	0.8255	0.7971
TA.Rg	458	2.9630	1.2138	8.1075	2.7363	1.7107	0.9848	0.8113
P/FCFE								
RoE	2 196	2.5570	0.9653	12.4714	4.8774	**1.0779**	0.7189	**0.7448**
TA	2 607	4.3438	1.0349	53.5996	12.3394	1.3553	0.8096	0.7823
Rg	1 927	8.3289	1.0154	215.7900	25.9085	1.3361	0.8068	0.7946
RoE.TA	656	**1.5833**	0.8850	**2.3926**	**1.5111**	1.0979	0.7248	0.8190
RoE.Rg	779	1.6439	**0.8448**	3.2650	1.9861	1.1128	**0.7078**	0.8378
TA.Rg	490	1.9551	1.0251	4.0096	2.0508	1.4000	0.8431	0.8224
P/FCFF								
RoE	2 188	2.6256	0.8607	16.3594	6.2307	1.0524	0.7031	**0.8169**
TA	2 596	2.9955	0.9228	21.7751	7.2692	1.1784	0.7754	0.8403
Rg	1 928	3.0497	0.8306	18.6091	6.1020	1.1898	0.7145	0.8602
RoE.TA	665	1.3761	0.7368	2.5739	1.8704	0.9097	**0.6055**	0.8218
RoE.Rg	787	**1.2718**	**0.7133**	**2.3656**	1.8601	**0.8691**	0.6117	0.8576
TA.Rg	520	1.3593	0.7690	2.4321	**1.7893**	1.0684	0.6949	0.9036
P/R								
RoE	2 167	1.3249	0.6737	6.2266	4.6998	0.5658	0.4013	0.5957
TA	2 394	1.3444	0.6951	5.4519	4.0551	**0.5181**	0.3724	0.5356
Rg	1 965	1.5219	0.6991	7.7131	5.0680	0.5227	**0.3615**	**0.5170**
RoE.TA	711	**0.8588**	0.5734	1.4602	1.7002	0.5581	0.4067	0.7092
RoE.Rg	811	1.0070	0.6070	2.1194	2.1045	0.5694	0.4190	0.6903
TA.Rg	598	1.2231	0.6824	3.4367	2.8097	0.5342	0.3754	0.5501

Note: The highlighted figures represent the optimal valuation fundamentals (exhibiting the lowest ε_{it})
for each measure of central tendency and dispersion.

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The prevalence of the outliers is an important observation since the mean (depicted as asterisks) is very susceptible to these outliers. Also note from Figure 5.1 that all 96 boxes are located significantly closer to the bottom end of the whiskers, indicating that the data are not symmetrically distributed, but positively skewed. These are the two main reasons that researchers generally focus on measures of central tendency other than the mean (Bhojraj & Lee, 2002; Liu *et al.,* 2002a; Beatty *et al.,* 1999). Consequently, this necessitated the use of a more robust measure of central tendency, such as the median.

After constructing six pools of valuation errors, based on the six valuation fundamentals-based peer groups, for each of the 16 multiples, the valuation performance of the 96 pools of valuation errors (ε_{it}) was analysed. It is evident from Figure 5.1 that all the multiples whose peer groups were based on a combination of valuation fundamentals indicated lower mean valuation errors than their corresponding single valuation fundamentals.[25]

In Figure 5.2 the scaling is adjusted to accommodate a more detailed analysis of the central 50% of the observations (the box areas). The red and blue notches in the box areas in Figure 5.2 indicate approximate 95% confidence levels for the medians (depicted as white horizontal lines in the boxes), which allows statistical inference. Note that all the median valuation errors in Figure 5.2 are lower than their corresponding mean valuation errors in Figure 5.1, which is the case for all 16 multiples. This observation results from the mean's greater susceptibility to outliers relative to the median, which is why the median is regarded as a more robust measure of central tendency.

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[25] The interval parameters for the top and bottom whiskers in Figure 5.1 are [P75 + 5 (P75 - P25); P25 - 5 (P75 - P25)]. The observations located outside these interval parameters are flagged as outliers. Note that the outliers occur only above the top whiskers in Figure 5.1. In addition, note that not all the asterisks are visible for the value drivers NCIfOA and OD in Figure 5.1. This is due to the size of the TA- and Rg-based mean valuation errors of the NCIfOA (5.8618 and 35.5839, respectively) and OD (22.1383 and 17.7100, respectively) value drivers in particular, which can be gleaned from Table 5.1. The asterisks for these two value drivers are therefore situated among the bubbles, i.e. above the top whiskers in Figure 5.1.
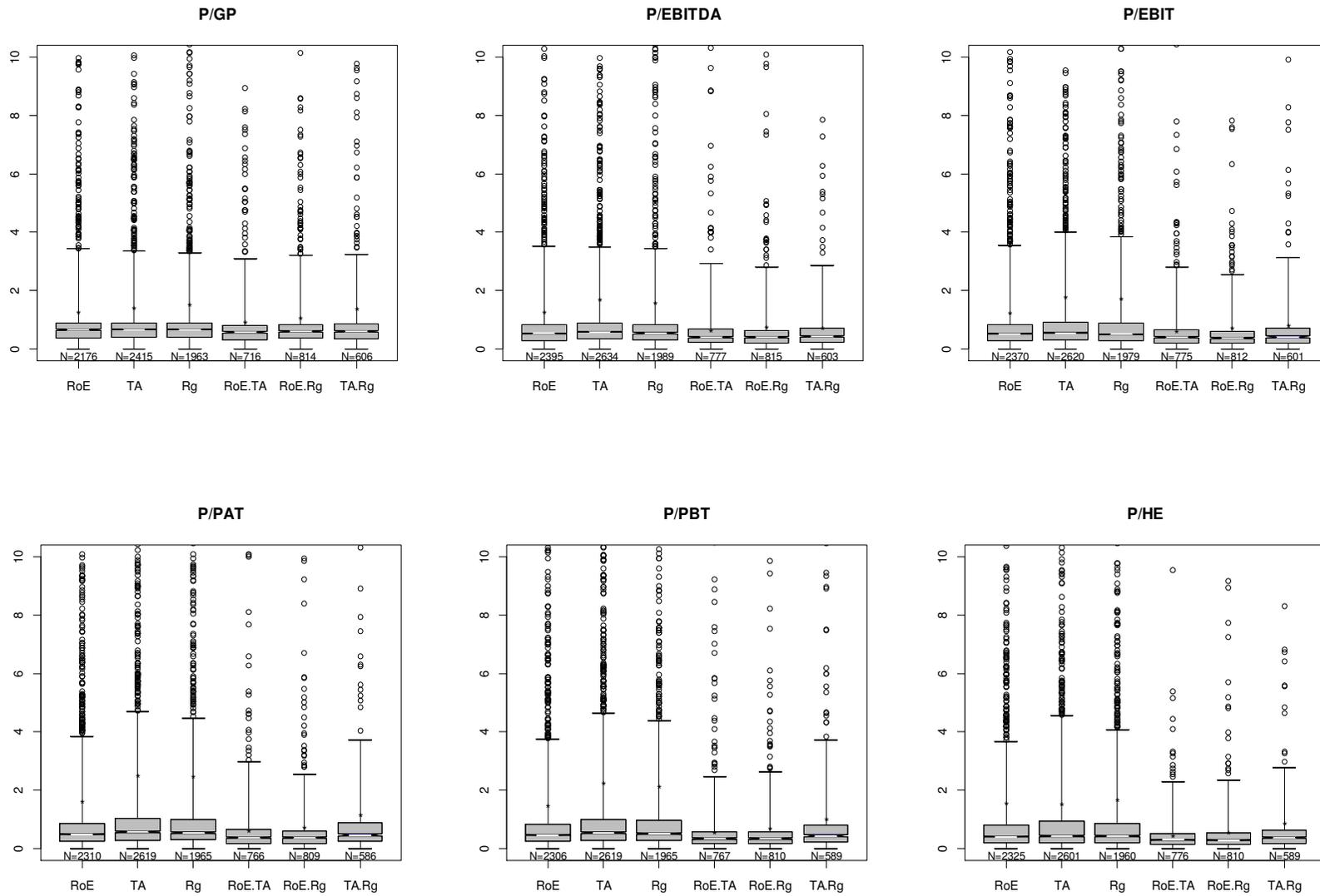
Figure 5.1: Absolute valuation errors over six valuation fundamentals (complete range)
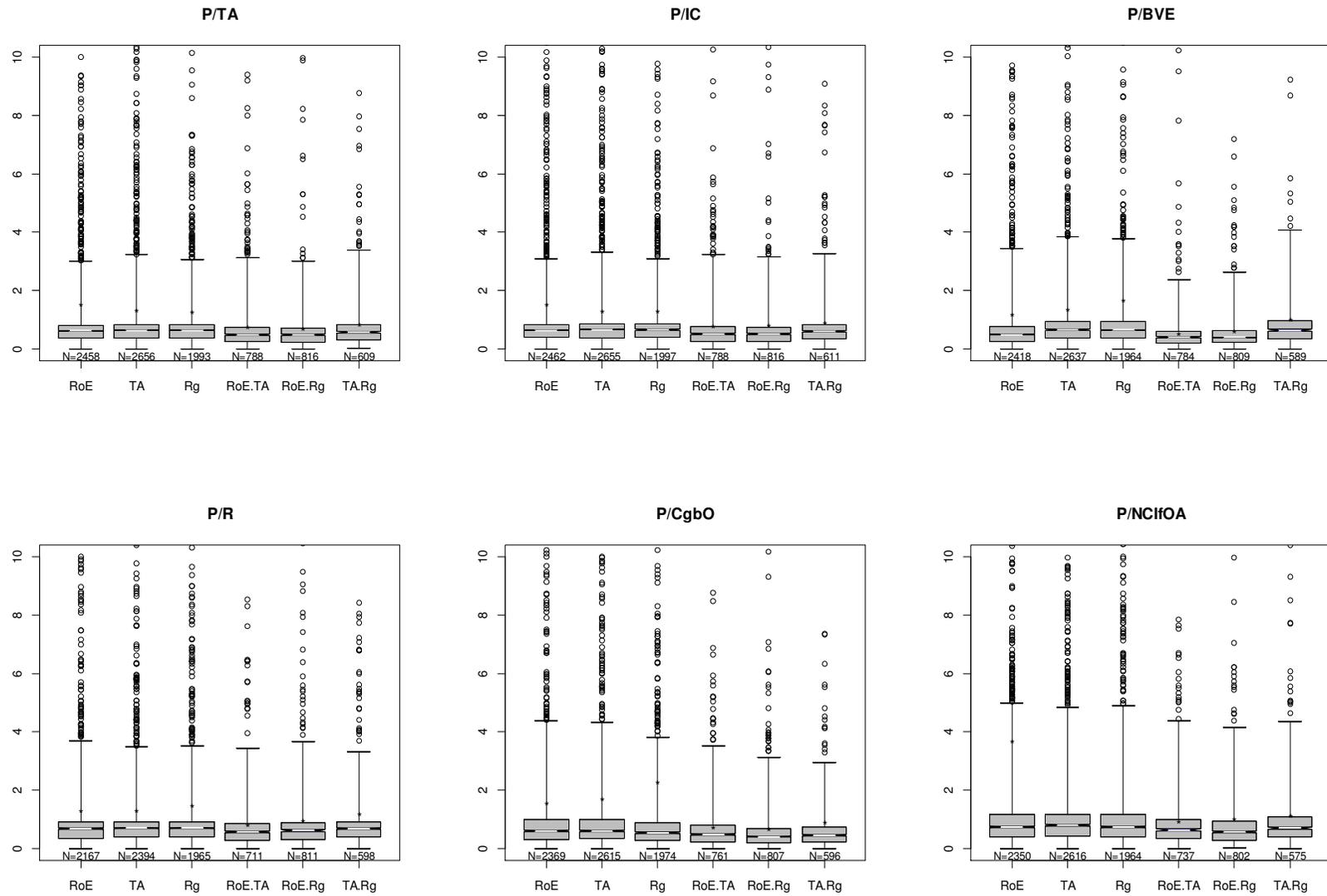
Figure 5.1…continued
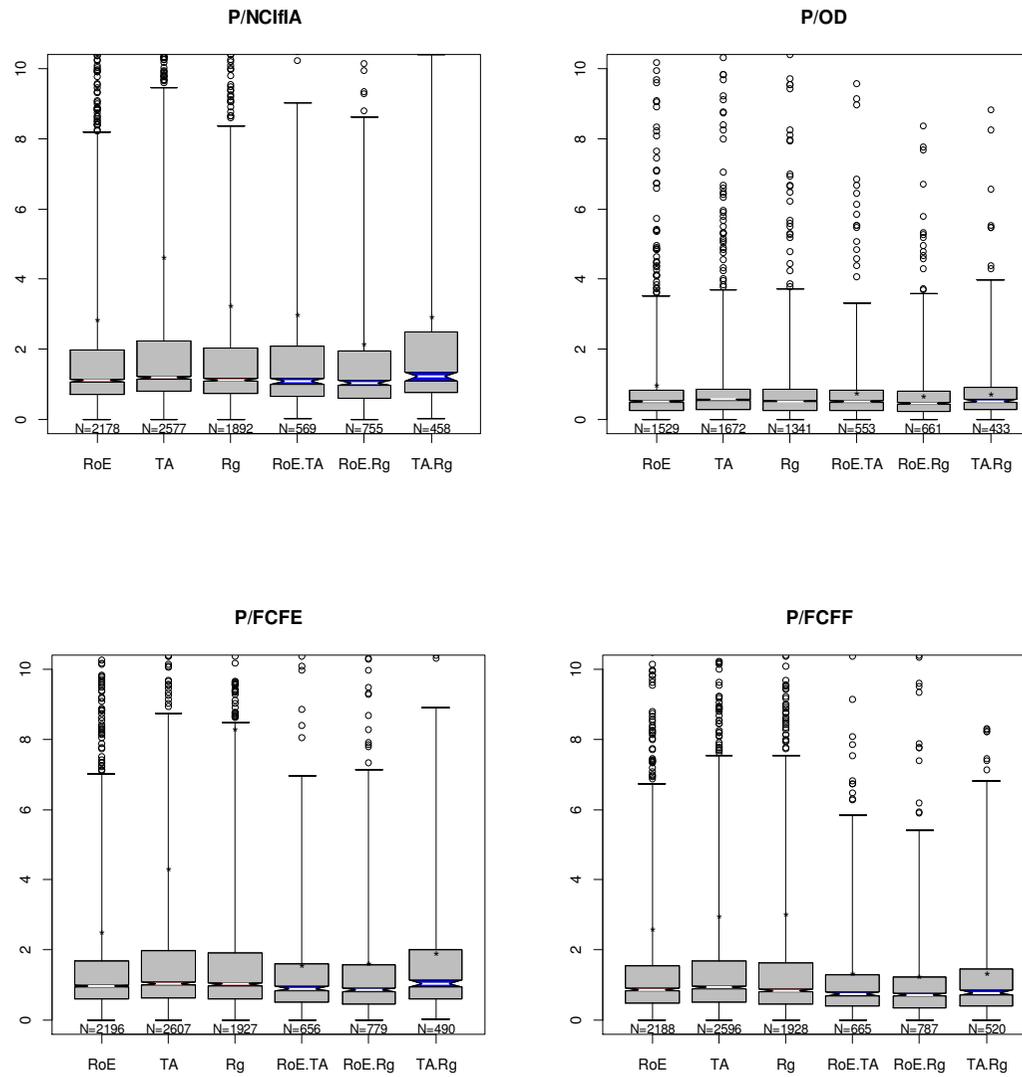
Figure 5.1…continued
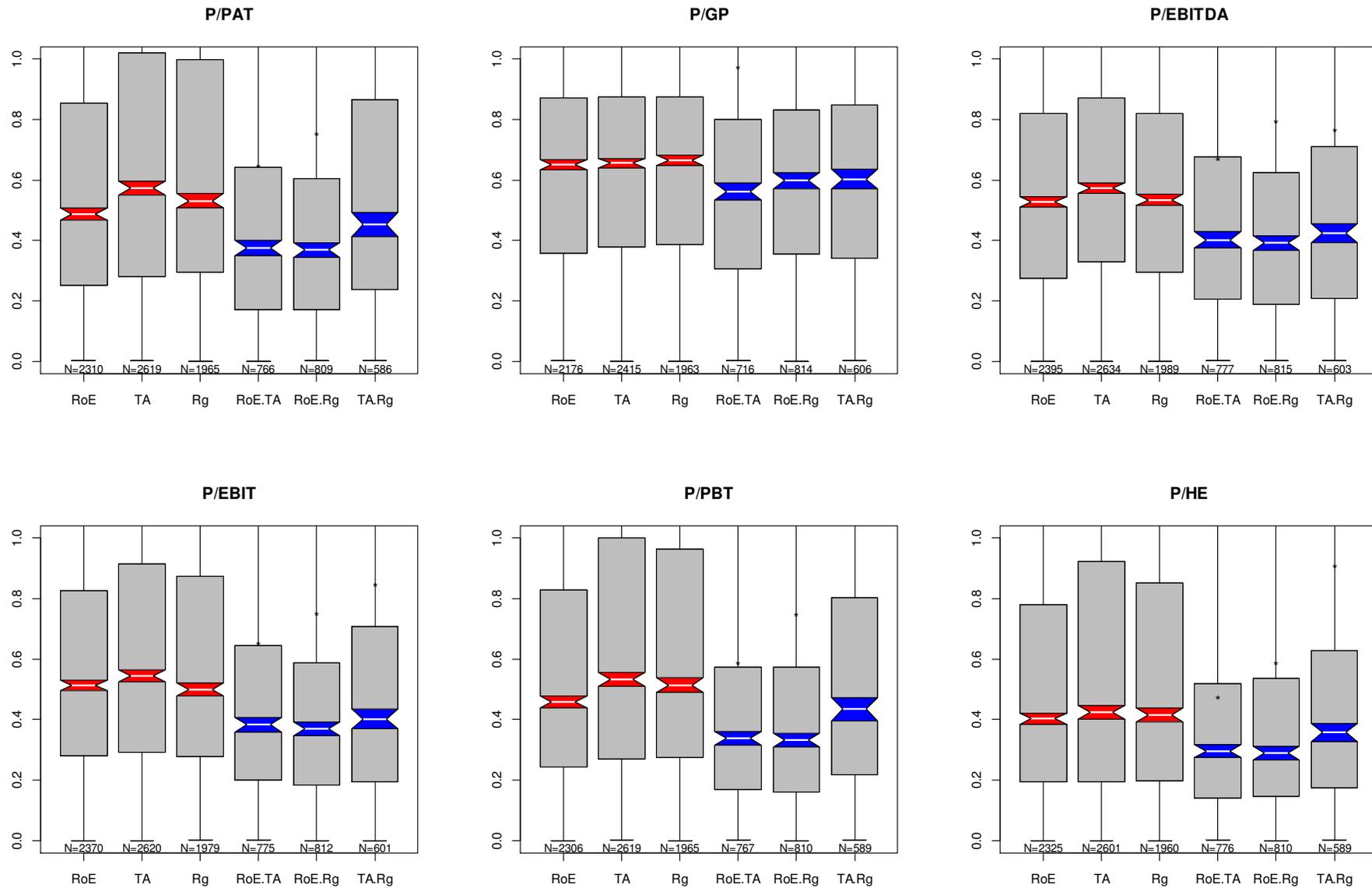
Figure 5.2: Absolute valuation errors over six valuation fundamentals (limited range focusing on the central 50% of the observations, i.e. the boxes)

Figure 5.2…continued

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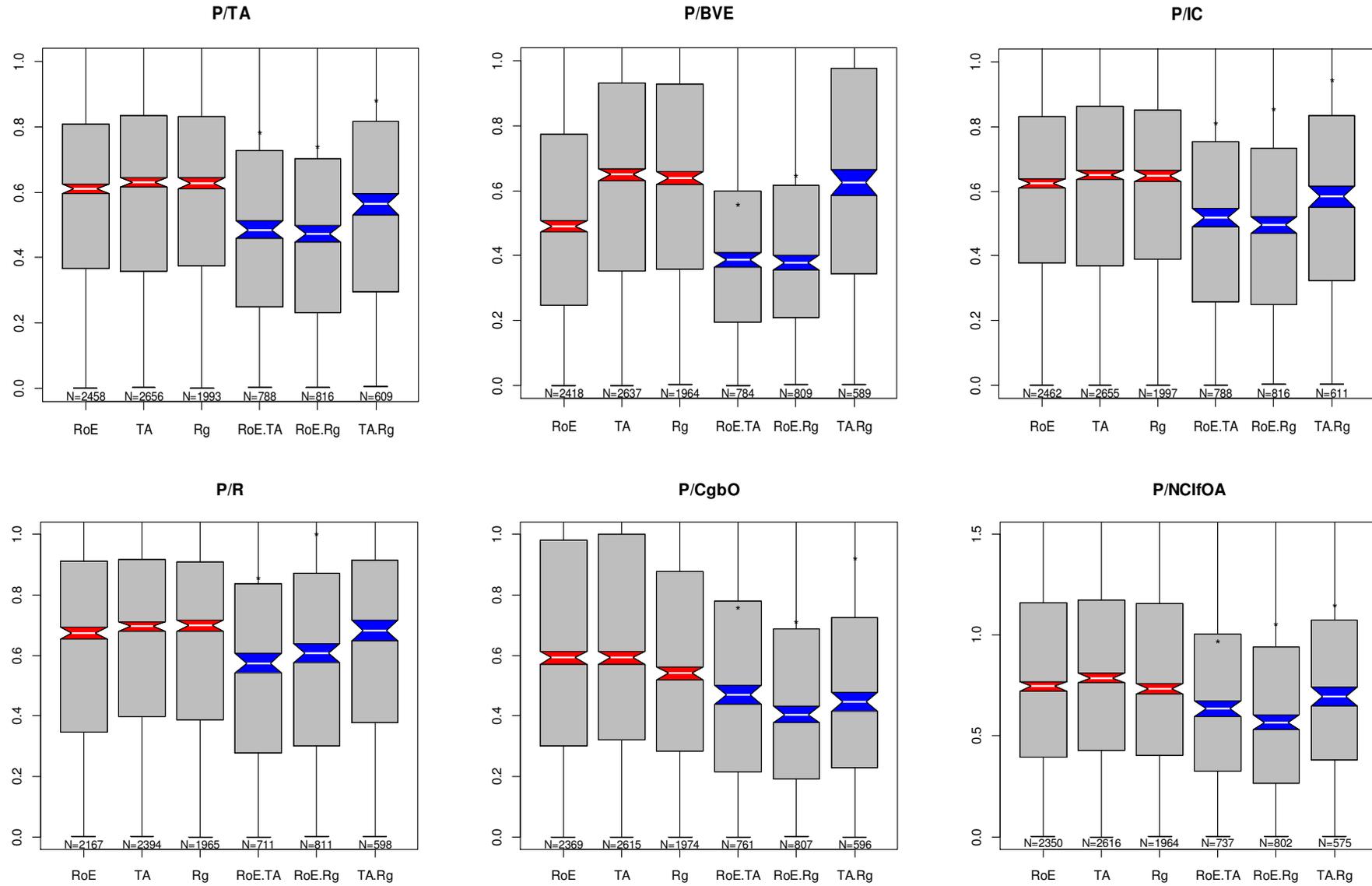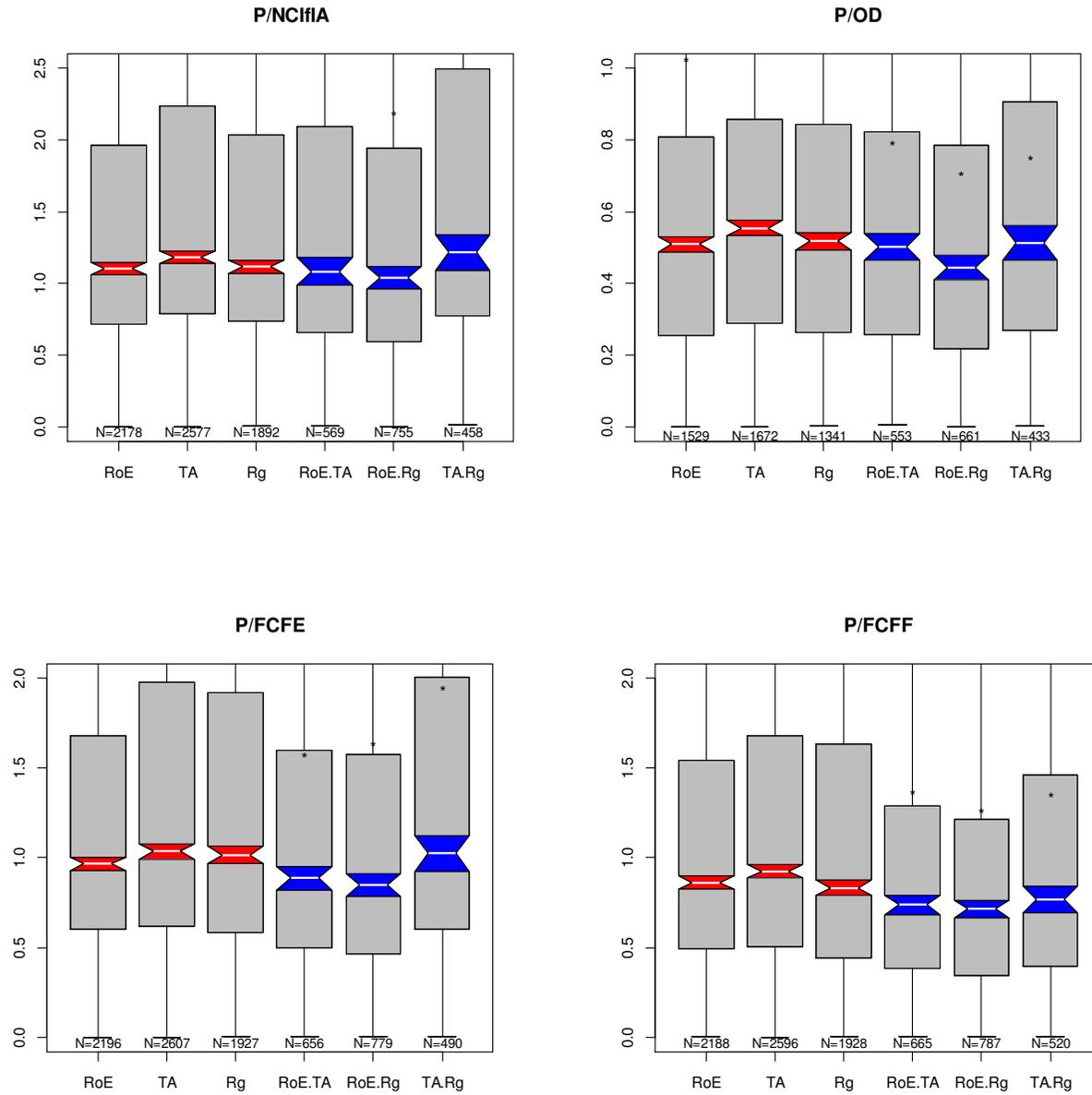
Figure 5.2…continued

Apart from the central tendency measures, the mean and the median, a measure of the dispersion of valuation errors is also needed. For example, while a pool of valuation errors based on single valuation fundamentals may have a similar mean or median to that of its combination of valuation fundamentals-based counterpart, the dispersion in their respective pools of valuation errors may be vastly different. Therefore, an analysis of the dispersion of the opposing pools of valuation errors is equally important since it offers insight as to how the data clusters around the mean or the median.

5.5.2   Dispersion of the data

For the sake of completeness, mean-based measures of dispersion are included in the analysis and depicted in Figure 5.3. However, as mentioned earlier, the focus of the analysis is on a comparison between the degree of dispersion around the median and the degree of variability between the single- and combination-based pools of valuation errors.

The radar graphs in Figure 5.3 depict the relative degree of dispersion between the 16 multiples whose peer group estimates were based on the three single valuation fundamentals (RoE, Rg and TA) and their corresponding peer group estimates that were based on the three combinations of valuation fundamentals (RoE.TA, RoE.Rg and TA.Rg). The two measures employed in this respect were the SD and the CV.

As is evident from Figure 5.3, the SD and the CV support the initial findings illustrated in Figure 5.2. Therefore, multiples whose peer group estimates are based on combinations of valuation fundamentals not only exhibit smaller valuation errors, but also display a lesser degree of dispersion and less variability relative to multiples whose peer group estimates are based on single valuation fundamentals. Equally evident from Figure 5.3, is that cash flow-based multiples exhibit a higher degree of variability compared to the other multiples. This phenomenon is explored in more detail in Chapter 7. However, these findings must be interpreted with the necessary caution, since the SD and the CV are susceptible to the same shortcomings as the

mean in the presence of outliers.
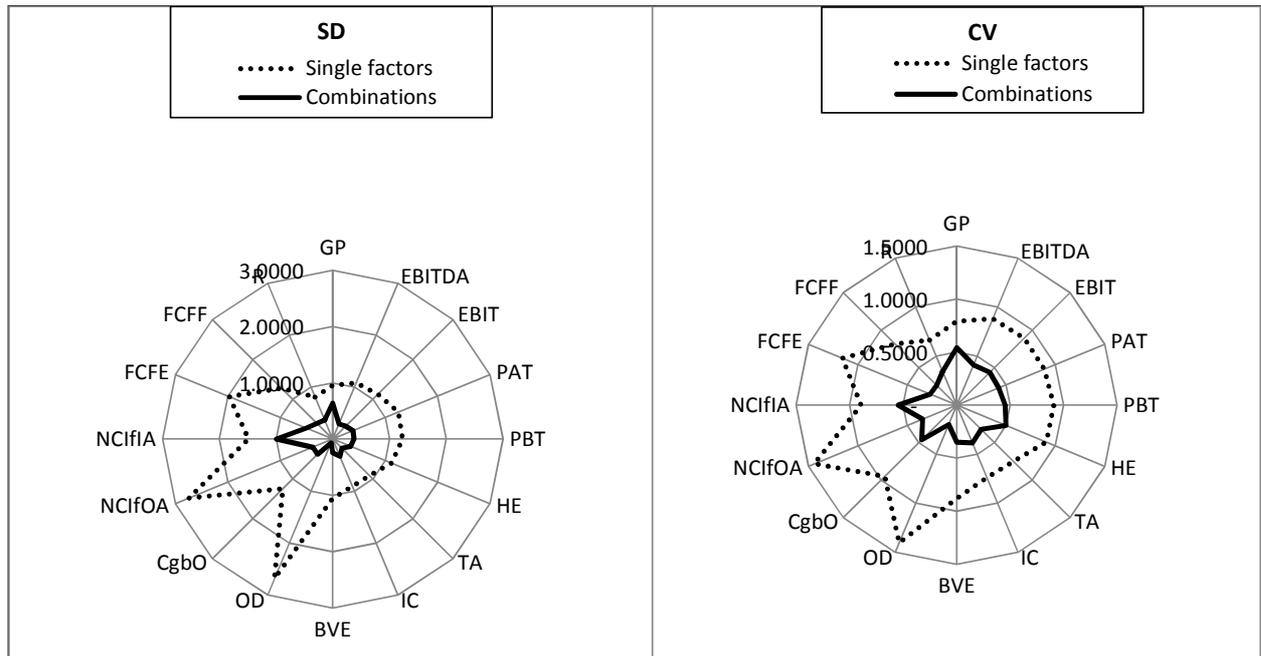
Figure 5.3: Variability of the valuation errors around the mean: Scale of ε_{it}

(SD) and fraction of the mean (CV)

Note: These two radar graphs are based on the logged ε_{it}.

Figure 5.4 depicts three measures that are generally regarded as more robust measures of dispersion, namely the IQR, the MAD and the CMAD. As is evident from Figure 5.4, multiples whose peer groups are based on a combination of valuation fundamentals display similar variations to multiples whose peer groups are based on single valuation fundamentals. Combination of valuation fundamentals-based multiples and single valuation fundamental-based multiples also exhibit a similar dispersion of valuation errors around the median, as measured by the CMAD, which is a more robust alternative to the CV.

5.5.3 The choice of valuation fundamental and the impact thereof on valuation accuracy

A relative comparison among the three single valuation fundamentals (depicted by the red-notched boxes in Figure 5.2) reveals that none consistently offered

statistically significant improvements of the median valuation error at the 95% confidence level. This can be gleaned from the fact that none of the three red-notched boxplots consistently offered the lowest median valuation error (without their red notches overlapping) for all 16 multiples. Among the single valuation fundamentals, only two offered instances of statistically significant improvements of the median at the 95% confidence level. RoE did so for two multiples, namely PBT and BVE, while Rg did so for only one multiple, namely CgbO. It is also evident from the opportunity cost analysis in Table 5.2 that RoE, on average, produced the most accurate valuations among the single valuation fundamentals, offering 7.18% and 2.99% more accurate valuations than TA and Rg, respectively.

Similarly, a relative comparison among the three combinations of valuation fundamentals (depicted by the blue-notched boxes in Figure 5.2) reveals that none of the combinations of valuation fundamentals consistently offered statistically significant improvements of the median at the 95% confidence level. From Table 5.2, it is evident that RoE.Rg produced the most accurate equity valuations among the combinations of valuation fundamentals, offering 15.08% more accurate valuations than TA.Rg and 3.64% more accurate equity valuations than RoE.TA.

A comparison of all six pools of valuation errors for each of the 16 multiples suggests that not all the combinations of valuation fundamentals offer statistically significant improvements of the median at the 95% confidence level *vis-à-vis* single valuation fundamentals. As is evident from Figure 5.2, when employing the TA.Rg combination, only three multiples offer improvements of statistical significance compared to single valuation fundamentals, namely EBITDA, EBIT and CgbO. The combination RoE.TA offers statistically significant improvements compared to single valuation fundamentals at the 95% confidence level for all but four cash flow-based multiples, namely NCIfIA, OD, FCFE and FCFF, while the combination RoE.Rg offers statistically significant improvements at the 95% confidence level for all but one cash flow-based multiple, namely NCIfIA.
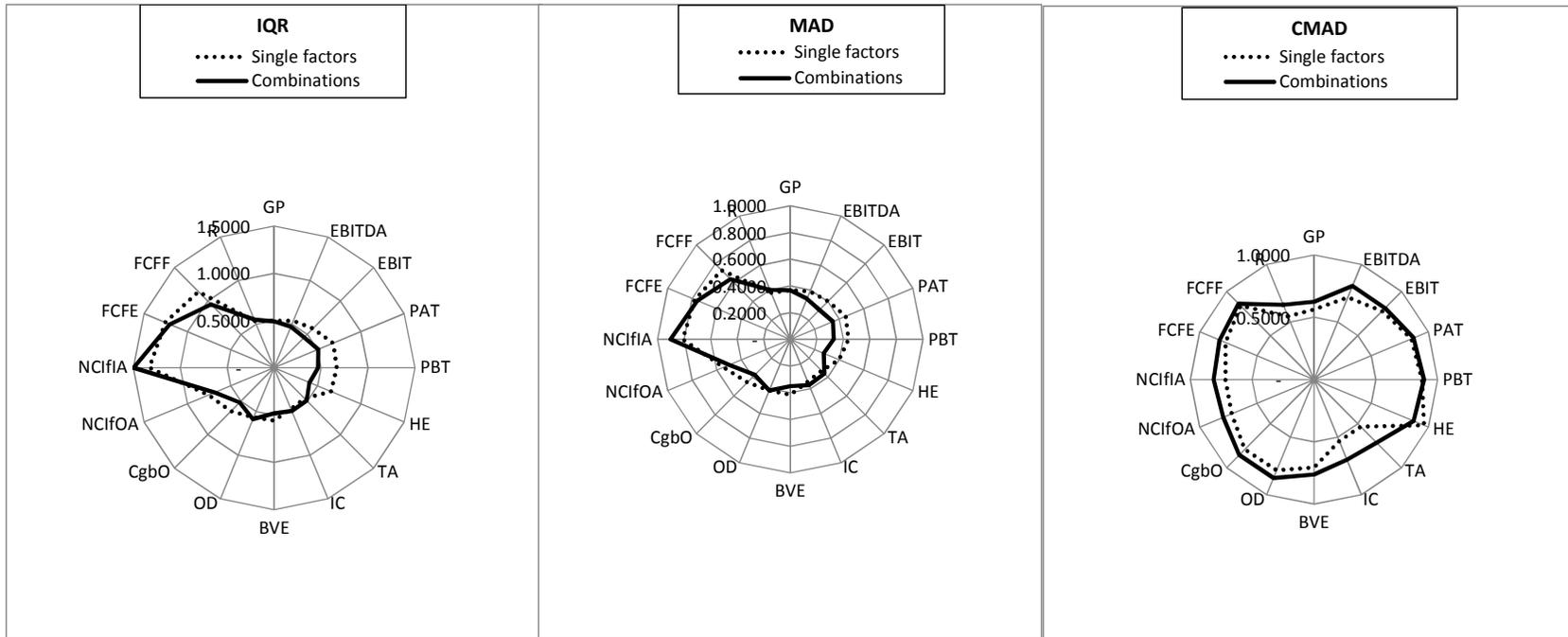
Figure 5.4: Variability of valuation errors around the median: Scale of ε_{it} **(IQR and MAD) and fraction of the median (CMAD)**

However, from Figures 5.1 and 5.2, it is evident that a combination of valuation fundamentals generally offers a greater degree of valuation accuracy *vis-à-vis* single valuation fundamentals. In Figure 5.1, the latter is reflected by a decrease in the means as the peer group selection shifts from single valuation fundamentals to a combination of valuation fundamentals. Similarly, the medians of two of the combinations of single valuation fundamentals, namely RoE.TA and RoE.Rg, are lower than that of the single valuation fundamentals for all of the multiples, while the combination TA.Rg exhibits lower medians for 68.75% of the multiples. Although the mean and the median rendered similar results, the results for the mean should be considered with the necessary caution, given its susceptibility to outliers. Consequently, although the mean is reported on, the primary focus of the analysis is on the median.

Table 5.2: Opportunity cost analysis reflecting the IMP offered by the optimal valuation fundamentals relative to the suboptimal valuation fundamentals

Value driver	IMP in single factors			IMP in combinations		
	RoE	TA	Rg	RoE.TA	RoE.Rg	TA.Rg
GP	15.71%	16.64%	18.24%	**0.00%**	6.47%	7.23%
EBITDA	34.88%	46.54%	36.41%	2.66%	**0.00%**	8.51%
EBIT	38.96%	47.67%	35.22%	3.61%	**0.00%**	9.00%
PAT	31.78%	55.02%	43.87%	1.68%	**0.00%**	22.56%
PBT	37.86%	60.10%	54.41%	1.78%	**0.00%**	30.54%
HE	39.47%	46.71%	43.84%	2.35%	**0.00%**	23.44%
TA	29.52%	33.59%	33.04%	2.71%	**0.00%**	19.38%
IC	26.18%	31.47%	30.85%	4.73%	**0.00%**	17.78%
BVE	29.24%	71.73%	69.22%	1.85%	**0.00%**	65.15%
OD	14.37%	24.47%	16.40%	12.73%	**0.00%**	15.14%
CgbO	46.16%	46.18%	33.49%	15.81%	**0.00%**	10.18%
NCIfOA	31.33%	38.74%	29.28%	11.69%	**0.00%**	22.57%
NCIfIA	6.40%	14.17%	7.74%	4.59%	**0.00%**	17.20%
FCFE	14.26%	22.50%	20.19%	4.76%	**0.00%**	21.34%
FCFF	20.66%	29.37%	16.44%	3.29%	**0.00%**	7.81%
R	17.49%	21.22%	21.92%	**0.00%**	5.86%	19.01%
Average						
Overall	27.14%	37.88%	31.91%	4.64%	0.77%	19.80%
Single factors	**0.00%**	7.18%	2.99%			
Combinations				3.64%	**0.00%**	15.08%

Table 5.2 contains a summary of the relative performance of the 16 multiples whose peer groups were constructed based on similar valuation fundamentals. It indicates the IMP in valuation accuracy that may be secured by substituting a suboptimal valuation fundamental with the most accurate valuation fundamental, i.e. by replacing a valuation fundamental with a larger valuation error (ε_{it}) with the valuation fundamental with the smallest valuation error (ε_{it}). The optimal valuation fundamentals are, therefore, indicated by zeros. Similar to the initial analysis in Figures 5.1 and 5.2, where the emphasis was on the smallest valuation error, the focus in Table 5.2 is on the valuation fundamental with the lowest IMP in valuation accuracy. Consequently, based on the median valuation errors, the positive percentages in Table 5.2 indicate to what extent the valuation accuracy of each multiple could be increased by selecting a peer group based on the optimal valuation fundamental.

The following can be gleaned from Table 5.2: Firstly, as was demonstrated in Figure 5.2, multiples whose peer groups are based on combinations of valuation fundamentals produce more accurate valuations than multiples whose peer groups are based on single valuation fundamentals. This is evident from the lower overall average IMP of the combinations of valuation fundamentals *vis-à-vis* the single valuation fundamentals and the fact that all the optimal valuation fundamentals, i.e. valuation fundamentals with zero IMPs, are combinations of valuation fundamentals, notably RoE.Rg and RoE.TA.

Secondly, the average IMP in valuation accuracy over all 16 multiples, when applying combinations of valuation fundamentals instead of single valuation fundamentals for RoE, Rg and TA, were all substantial, at 27.14%, 31.91% and 37.88%, respectively. Thirdly, the combination of valuation fundamentals that produced the most accurate valuations is RoE.Rg, reflecting an average IMP in valuation accuracy over all 16 multiples of 0.77%, which is negligible. Similarly, the combination RoE.TA indicates a 4.64% IMP, which is also insubstantial. Finally, the combination of valuation fundamentals TA.Rg is substantially less accurate than the combinations RoE.TA and RoE.Rg, with an average IMP of 19.80%. Although no combination of valuation fundamentals produced the most accurate valuations

across all 16 multiples, the optimal choice of valuation fundamentals was the combination RoE.Rg, which was optimal for 87.5% of the multiples, followed by the combination RoE.TA, which was optimal for the remaining 12.5% of the multiples.

The magnitude of the IMP in valuation accuracy that a careful selection of valuation fundamentals could secure becomes even more apparent when considering individual multiples. For example, when employing P/BVE, the median-based valuation accuracy of the multiple can be improved by between 29.24% and 71.73% when switching from single valuation fundamental-based peer groups to the combination of valuation fundamentals-based peer group RoE.Rg. The IMP indicated in Table 5.2, together with the similar dispersion patterns exhibited by the IQR, the MAD and the CMAD, supports the earlier findings illustrated in Table 5.1 and Figures 5.1 and 5.2.[26]

The evidence therefore suggests that multiples whose peer groups are based on a combination of valuation fundamentals exhibit superior explanatory power *vis-á-vis* multiples whose peer groups are based on single valuation fundamentals. This is confirmed by the fact that multiples whose peer groups are based on a combination of valuation fundamentals consistently offered more accurate results than their single valuation fundamentals-based counterparts over all 16 multiples. In addition, an analysis of the dispersion of the valuation errors indicated that multiples whose peer groups are based on a combination of valuation fundamentals display a similar degree of variability to their single valuation fundamental-based counterparts.

The most plausible reason for the superior valuation performance of multiples whose peer groups are based on a combination of valuation fundamentals is that they help define more homogeneous peer groups, i.e. peer groups that resemble more closely the characteristics of the target entity. Accordingly, one would be inclined to argue that a combination of all three valuation fundamentals, namely RoE.TA.Rg, may offer

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[26] Although the SD and CV observations consistently exhibited a smaller variation in the explanatory power of a combination of valuation fundamentals-based multiples over single valuation fundamental-based multiples, one needs to take cognisance of the fact that the mean, the SD and the CV are unduly influenced by outliers, which, as suggested by the bubbles in Figure 5.1, were quite prevalent.

an even higher degree of valuation accuracy. Unfortunately, due to the limited depth of the South African market, the number of peer groups produced by the combination RoE.TA.Rg was negligible and it was consequently excluded from the analysis.

5.5.4 Peer group selection: valuation fundamentals versus industry classification

A comparison between the valuation accuracy of multiples whose peer groups are based on valuation fundamentals with that of multiples whose peer groups are based on industry classification is summarised in Table 5.3. The 10 Peer Group Variables (PGVs), six valuation fundamentals and four industry classifications are ranked from least accurate PGV to the most accurate PGV, indicating the IMP that may be secured when substituting each suboptimal choice of PGV with the optimal PGV. Therefore, the least accurate choice of PGV is situated furthest to the left of Table 5.3 and carries the highest IMP, while the optimal choice of PGV is situated furthest to the right and carries no IMP, i.e. the IMP is zero.

The following can be gleaned from Table 5.3: Firstly, multiples whose peer groups are based on single valuation fundamentals generally perform the least accurate equity valuations. This is reflected in a suboptimal IMP range of 12.57% to 41.77% and the fact that none of the multiples whose peer groups were based on single valuation fundamentals produced the most accurate valuation for any of the 16 multiples. Secondly, multiples whose peer groups are based on industry classifications generally perform more accurate valuations than multiples whose peer groups are based on single valuation fundamentals, but less accurate valuations than multiples whose peer groups are based on a combination of valuation fundamentals. Multiples whose peer groups are based on industry classifications indicate a suboptimal IMP, ranging from 0.58% to 36.09%, and produced the most accurate valuations for three, or 18.75%, of the multiples, namely NCIfIA, FCFE and FCFF. Thirdly, multiples whose peer groups are based on a combination of valuation fundamentals generally perform more accurate valuations than multiples whose peer groups are based on industry classifications, culminating in a suboptimal IMP ranging

Table 5.3: IMP in the median valuation errors based on 10 PGVs

GP									
Peer group	Rg	TA	RoE	IND	SUB	SUP	SEC	TA Rg	RoE Rg	RoE TA
IMP	15.43%	14.26%	13.58%	12.80%	10.87%	9.31%	9.13%	6.74%	6.07%	0.00%
N	1963	2415	2176	2356	1790	2338	2235	606	814	716

EBITDA									
Peer group	TA	Rg	RoE	IND	SUP	SEC	SUB	TA Rg	RoE TA	RoE Rg
IMP	31.76%	26.69%	25.86%	22.17%	19.11%	17.73%	14.81%	7.85%	2.59%	0.00%
N	2634	1989	2395	2345	2328	2229	1768	603	777	815

EBIT									
Peer group	TA	RoE	Rg	IND	SUP	SEC	SUB	TA Rg	RoE TA	RoE Rg
IMP	32.28%	28.04%	26.05%	20.81%	16.14%	15.86%	13.20%	8.26%	3.48%	0.00%
N	2620	2370	1979	2276	2259	2161	1723	601	775	812

PAT									
Peer group	TA	Rg	RoE	TA Rg	IND	SUP	SUB	SEC	RoE TA	RoE Rg
IMP	35.49%	30.49%	24.12%	18.41%	14.39%	12.85%	12.17%	11.94%	1.65%	0.00%
N	2619	1965	2310	586	2128	2112	1609	2015	766	809

PBT									
Peer group	TA	Rg	RoE	TA Rg	IND	SUP	SUB	SEC	RoE TA	RoE Rg
IMP	37.54%	35.24%	27.46%	23.40%	21.05%	18.61%	18.25%	18.17%	1.74%	0.00%
N	2619	1965	2306	589	2159	2142	1613	2043	767	810

HE									
Peer group	TA	Rg	RoE	TA Rg	SUB	SEC	SUP	IND	RoE TA	RoE Rg
IMP	31.84%	30.48%	28.30%	18.99%	14.43%	8.49%	8.03%	7.73%	2.30%	0.00%
N	2601	1960	2325	589	1656	2064	2162	2178	776	810

TA									
Peer group	TA	IND	Rg	RoE	SUP	SEC	SUB	TA Rg	RoE TA	RoE Rg
IMP	25.14%	24.88%	24.83%	22.79%	21.49%	18.03%	17.35%	16.23%	2.64%	0.00%
N	2656	2684	1993	2458	2664	2589	2142	609	788	816

IC									
Peer group	IND	TA	Rg	SUP	RoE	SEC	SUB	TA Rg	RoE TA	RoE Rg
IMP	24.15%	23.94%	23.58%	20.98%	20.75%	16.90%	16.62%	15.09%	4.51%	0.00%
N	2682	2655	1997	2662	2462	2588	2163	611	788	816

BVE									
Peer group	TA	Rg	TA Rg	SEC	SUB	IND	SUP	RoE	RoE TA	RoE Rg
IMP	41.77%	40.91%	39.45%	36.09%	35.06%	34.45%	34.23%	22.63%	1.82%	0.00%
N	2637	1964	589	2303	1879	2409	2389	2418	784	809

R									
Peer group	Rg	TA	TA Rg	IND	RoE	SUP	SEC	SUB	RoE Rg	RoE TA
IMP	17.98%	17.51%	15.97%	15.45%	14.89%	10.38%	9.21%	8.24%	5.54%	0.00%
N	1965	2394	598	2386	2167	2366	2263	1813	811	711

CgbO									
Peer group	TA	RoE	Rg	SUB	SEC	IND	SUP	RoE TA	TA Rg	RoE Rg
IMP	31.59%	31.58%	25.09%	20.67%	18.99%	18.84%	18.76%	13.65%	9.24%	0.00%
N	2615	2369	1974	1626	2012	2171	2155	761	596	807

NCIfOA									
Peer group	TA	RoE	Rg	TA Rg	RoE TA	SEC	SUB	SUP	IND	RoE Rg
IMP	27.92%	23.85%	22.65%	18.42%	10.47%	8.31%	7.93%	7.57%	4.78%	0.00%
N	2616	2350	1964	575	737	1818	1425	1937	1952	802

NCIfIA									
Peer group	TA Rg	TA	Rg	RoE	RoE TA	RoE Rg	SUB	SUP	SEC	IND
IMP	37.44%	35.78%	31.95%	31.09%	29.89%	26.68%	6.94%	2.35%	1.27%	0.00%
N	458	2577	1892	2178	569	755	724	1094	994	1110

OD									
Peer group	SUB	TA	SUP	SEC	Rg	TA Rg	IND	RoE	RoE TA	RoE Rg
IMP	20.96%	19.66%	18.36%	17.02%	14.09%	13.15%	12.98%	12.57%	11.29%	0.00%
N	1176	1672	1661	1504	1341	433	1682	1529	553	661

FCFE									
Peer group	TA	TA Rg	Rg	RoE	RoE TA	RoE Rg	SUB	SEC	IND	SUP
IMP	34.27%	33.65%	33.01%	29.53%	23.14%	19.48%	4.67%	0.83%	0.58%	0.00%
N	2607	490	1927	2196	656	779	921	1249	1384	1372

FCFF									
Peer group	TA	RoE	Rg	TA Rg	RoE TA	RoE Rg	SUB	SEC	SUP	IND
IMP	34.37%	29.64%	27.09%	21.25%	17.81%	15.10%	6.96%	3.69%	1.66%	0.00%
N	2596	2188	1928	520	665	787	1030	1400	1544	1556

from 1.65% to 39.45%, and produced the most accurate valuations for 13, or 81.25%, of the multiples.

Although Table 5.3 reflects the magnitude of the increase in valuation accuracy that a careful selection of peer group entities may produce, each of the 16 multiples displays 10 data points, which obscures a comprehensive grasp of the relative valuation performance of the 10 PGVs for each multiple. The multi-dimensional nature of the data contained in Table 5.3 complicates a careful analysis of the general trend of the data. Since the data occupies multi-dimensional space, i.e. it encapsulates multiple coordinate axes, the use of a conventional two-dimensional scatter plot is inappropriate (Gower, Lubbe & Le Roux, 2011). However, the use of biplots accommodates higher-dimensional data by approximating it in lower, usually two-dimensional space, thereby enabling the visualisation of multi-dimensional data. The interpretation of biplots is considered in Section 5.5.4.1.

5.5.4.1 Interpreting biplots

Biplots accommodate the graphical display of information on the rows and columns of a data matrix. In a biplot, the rows and columns of a data matrix are displayed as data points and calibrated axes. The actual valuation errors underlying Table 5.3, i.e. the median valuation errors of all 16 multiples whose peer groups were based on 10 different PGVs, are contained in Table 5.4. Figure 5.5 depicts the transposed data contained in Table 5.4 in a two-dimensional PCA biplot, which offers a far clearer display of the data summary contained in Table 5.4.

a.   Calibrated axes

In Figure 5.5, the 16 multiples are depicted as 16 axes, calibrated in the original units of measurement. The following can be gleaned from the axes: Firstly, note the range of median valuation errors indicated on the axes. The ranges for some axes are wider than for others, suggesting that those with the smaller ranges, i.e. the smaller valuation errors, produced the more accurate valuations.

Table 5.4: Actual valuation errors of 16 multiples whose peer groups were based on 10 different PGVs

Multiple	PGV									
	RoE	**TA**	**Rg**	**RoE.TA**	**RoE.Rg**	**TA.Rg**	**IND**	**SUP**	**SEC**	**SUB**
GP	0.6496	0.6548	0.6638	0.5614	0.5977	0.6020	0.6438	0.6190	0.6178	0.6299
EBITDA	0.5275	0.5731	0.5335	0.4015	0.3911	0.4244	0.5025	0.4835	0.4754	0.4591
EBIT	0.5125	0.5446	0.4987	0.3821	0.3688	0.4020	0.4657	0.4398	0.4383	0.4249
PAT	0.4860	0.5717	0.5306	0.3750	0.3688	0.4520	0.4308	0.4232	0.4188	0.4199
PBT	0.4581	0.5320	0.5131	0.3382	0.3323	0.4338	0.4209	0.4083	0.4061	0.4065
HE	0.4028	0.4237	0.4154	0.2956	0.2888	0.3565	0.3130	0.3140	0.3156	0.3375
TA	0.6108	0.6300	0.6274	0.4844	0.4716	0.5630	0.6278	0.6007	0.5753	0.5706
IC	0.6246	0.6508	0.6477	0.5184	0.4950	0.5830	0.6526	0.6264	0.5957	0.5937
BVE	0.4888	0.6495	0.6400	0.3852	0.3782	0.6246	0.5770	0.5750	0.5918	0.5824
R	0.6737	0.6951	0.6991	0.5734	0.6070	0.6824	0.6782	0.6398	0.6316	0.6249
CgbO	0.5918	0.5919	0.5405	0.4689	0.4049	0.4461	0.4989	0.4984	0.4998	0.5104
NCIfOA	0.7458	0.7879	0.7342	0.6343	0.5679	0.6961	0.5964	0.6144	0.6194	0.6168
NCIfIA	1.1020	1.1825	1.1159	1.0832	1.0357	1.2138	0.7594	0.7777	0.7692	0.8160
OD	0.5085	0.5534	0.5175	0.5012	0.4446	0.5119	0.5109	0.5446	0.5358	0.5625
FCFE	0.9653	1.0349	1.0154	0.8850	0.8448	1.0251	0.6842	0.6802	0.6859	0.7135
FCFF	0.8607	0.9228	0.8306	0.7368	0.7133	0.7690	0.6056	0.6158	0.6288	0.6509
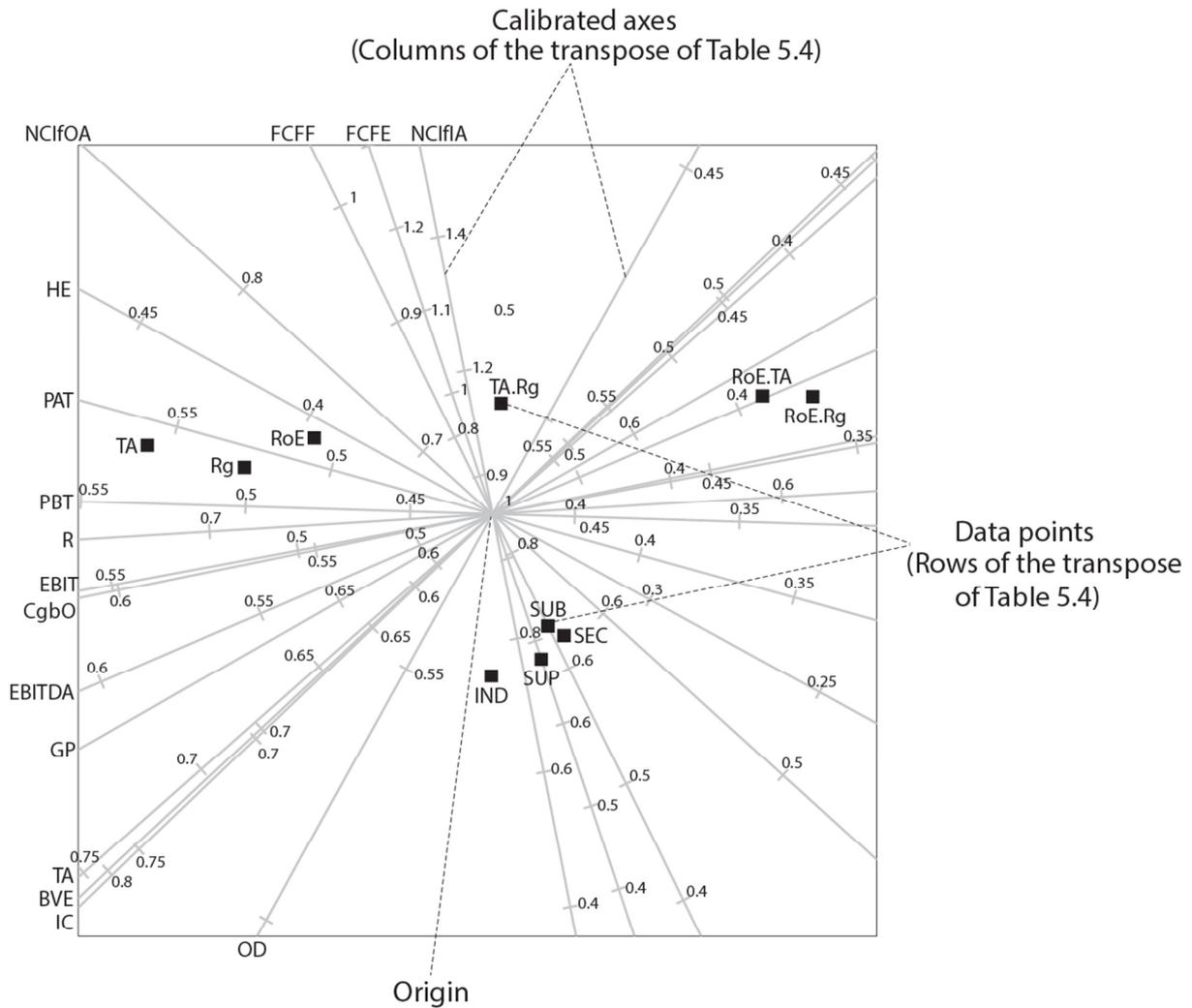
Figure 5.5: PCA biplot of multiples whose peer groups are based on 10 different PGVs

The data points on the OD axis, for example, indicate a valuation error range of approximately 0.47 to 0.54, while the data points on the FCFE axis indicate a range of approximately 0.68 to 1.08. From these ranges one is able to deduce that OD-based multiples produced more accurate valuations than FCFE-based multiples.

Secondly, note that the origin, which is positioned at the intersection of the 16 axes, reflects the average median valuation error of all 16 multiples, as depicted by the 16 axes. This allows for the comparison of the individual valuation performance of each multiple to the average valuation performance of all 16 multiples. The individual valuation performances of the multiples could, therefore, be classified as good (below average valuation error), average (close to average valuation error) or poor

(above average valuation error), relative to the average valuation performance. The calibrations on the axes afford one the opportunity to read the value of any particular variable for any point in the display. The latter is elaborated on in Section 5.5.4.1c.

Thirdly, note that the direction of the valuation error ranges is not the same for all multiples. While the valuation error range of OD, for example, increases from the top right quadrant to the bottom left quadrant, the valuation error range of NCIfIA increases from the bottom right quadrant to the top left quadrant. The legends of the calibrated axes indicate where the top ends of the valuation error ranges lie, i.e. where the larger valuation errors will be situated. Consequently, the legend for the OD axis is situated at the bottom end of the axis, while that of the NCIfIA axis is situated at the top end of the axis.

Fourthly, note that the angle between any two of the 16 axes is an indication of the correlation between the multiples. Small angles are indications of high correlation, while angles approaching orthogonality are an indication of poor correlation. The asset-based axes (TA, BVE and IC), for example, are all positioned tightly together, with very small angles. This suggests that they are highly positively correlated. As the angles between the axes widen and become more orthogonal, the correlations decline. The angle between the EBITDA and NCIfIA axes, for example, is almost orthogonal, which suggest that their correlation is almost zero.

However, a careful consideration of the angles between the axes is warranted. A hasty view of the angle between the axes NCIfIA and OD, for example, might lead one to conclude that they have a relatively weak positive correlation, which would be wrong. As mentioned before, the direction of the valuation error ranges of these two multiples differs. This suggests that these two multiples are not positively correlated. They have surpassed orthogonality and are, in fact, negatively correlated. However, in the conventional PCA biplot, the focus is on the positions of the data points, rather than that of the axes. Therefore, caution must be taken not to over-interpret the angles between the axes, because the conventional form of the PCA biplot is not constructed to optimally represent the angles in a two dimensional display. In order to visualise the optimal representation of the correlation among the axes, a correlation monoplot, which is discussed in Section 5.5.4.1d, should be constructed.

b.   Data points

The focus of the PCA biplot in Figure 5.5 is on the data points (representing the PGVs) and their relationship with the calibrated axes (representing the multiples). Note that Figure 5.5 is depicted based on the transpose of Table 5.4. The 10 data points (PGVs) are positioned relative to each other and the origin. Note that the data points' positions are displayed optimally, i.e. the relative distances between them and relative to the origin is optimised by default so that they are presented in the PCA biplot in the best possible two-dimensional space.

The following can be gleaned from the positions of the 10 data points: Firstly, consider the positions of the data points relative to the origin. Data points that are situated in the proximity of the origin suggest that multiples whose peer groups were based on these PGVs produced average valuation performances, while data points that are situated further away from the origin suggest either an above or below average valuation performance. In order to determine whether data points that are situated further away from the origin constitute an above or below average performance, one should consider their location in conjunction with the readings from the axes. In the case of the PBT multiple, for example, data points that are situated in close proximity to the origin, such as TA.Rg, reflect average valuation performances. Data points that are situated further away and to the right of the origin, such as RoE.Rg, reflect good results (above average valuation performances), while data points situated further away and to the left of the origin, such as TA, produced poor results (below average valuation performances).

However, when considering the valuation performance of the NCIfIA multiple, it is evident that data points that are situated above the origin offer a below average valuation performance, while data points situated below the origin, offer an above average valuation performance.

In order to assess the valuation performance of the individual multiples based on each of the 10 PGVs, it is first necessary to determine the direction of their valuation performance. All 16 axes indicate increased valuation errors as one moves horizontally from right to left on the axes. Consequently, one can deduce that the

valuation performance of these multiples, whose peer groups are based on the data points that are situated to the right of the origin, are good. Conversely, multiples whose peer groups are based on data points that are situated to the left of the origin can be classified as poor. The opposite would apply if the direction of the multiples' valuation performance was from left to right.

It is equally important to consider the direction of the multiples' valuation performance from a vertical perspective. The nine axes, starting from the OD axis and moving clockwise around the biplot up towards the R axis, display an increase in valuation errors as one moves from the top to the bottom of the axes. Consequently, one can deduce that the valuation performance of these nine multiples is good when their peer groups are based on the data points that are situated above the origin and poor when their peer groups are based on the data points that are situated below the origin.

Conversely, the remaining seven axes display an increase in valuation errors as one moves from the bottom to the top of the axes. Consequently, when these multiples' peer groups are based on data points that are situated below the origin their valuation performance can be classified as good, whereas they can be classified as poor when their peer groups are based on data points that are situated above the origin. Therefore, it is evident that the position of the data points should be viewed in conjunction with the readings from the axes.

Note that the biplot in Figure 5.5 does not display the actual data set, as contained in Table 5.4, which, geometrically, lies in a ten-dimensional space, but rather an approximation of the data in two dimensions. Although a certain loss of information is, therefore, inevitable when employing biplots, they are able to accommodate more than two variables in the form of calibrated axes, which would not be able to intersect orthogonally in two dimensions. Although the PCA-based biplot in Figure 5.5 approximates the data in the best possible two-dimensional space, the reduction of the multi-dimensionality of the data culminates in a loss of data accuracy (Greenacre, 2007). If the loss of information resulting from this approximation is negligible, much can be learned about the multi-dimensional nature of the data.

c.　　　Evaluating the quality of the biplots

In order to assess the loss of information accompanying the use of PCA biplots, one must consider the biplot's overall quality of display, the accuracy of its calibrated axes and that of its sample predictions. A higher overall quality of display reading reflects a less significant loss in data accuracy, and, *vice versa*. In Figure 5.5 the quality of display is 88.67%, which reflects the proportion of the total variation in the data accounted for in the remaining eight dimensions. The accuracy of the approximations of the individual axes in the biplot is known as the axes predictivities. These values, which can be obtained from the output of the *PCAbipl* function in the *R-package,* are contained in Table 5.5.[27]

Table 5.5: Predictivity readings over 16 multiples

Multiple	Predictivity
GP	0.822
EBITDA	0.928
EBIT	0.910
PAT	0.979
PBT	0.979
HE	0.969
TA	0.963
IC	0.957
BVE	0.703
R	0.773
CgbO	0.765
NCIfOA	0.952
NCIfIA	0.972
OD	0.573
FCFE	0.974
FCFF	0.970

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[27]　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
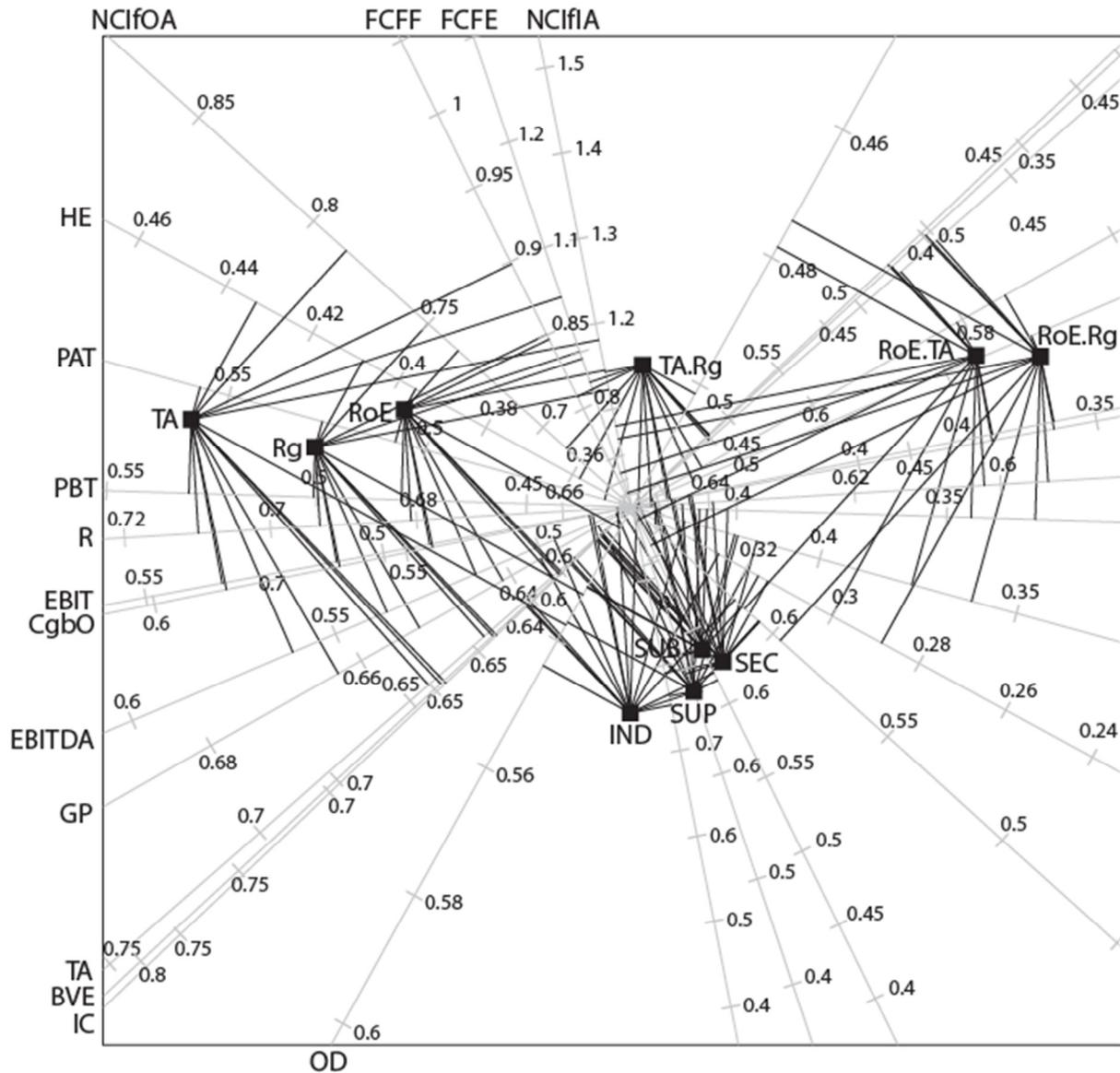
Figure 5.6: PCA biplot of multiples whose peer groups are based on 10 different PGVs (all sample predictions included)

The greatest loss in accuracy occurs with OD, and, at 57.3% it indicates that the presentation of OD is the poorest of all the multiples. The quality of display reading and the axes predictivity readings as contained in Table 5.5, confirmed a negligible loss of data accuracy.

Predictions can be read from the PCA biplot by projecting from a sample point onto any axes and obtaining a reading off the nearest marker on these axes. A good approximation will result in good predictions. The approximations of the actual data

Table 5.6: PGVs: Actual (Act) and Predicted (Pre) valuation errors over 16 multiples

Multiple	PGV									
	RoE		TA		Rg		RoE.TA		RoE.Rg	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre	Act	Pre
GP	0.6496	0.6369	0.6548	0.6624	0.6638	0.6517	0.5614	0.5808	0.5977	0.5742
EBITDA	0.5275	0.5068	0.5731	0.5598	0.5335	0.5367	0.4015	0.3922	0.3911	0.3777
EBIT	0.5125	0.4809	0.5446	0.5327	0.4987	0.5087	0.3821	0.3725	0.3688	0.3573
PAT	0.4860	0.4972	0.5717	0.5589	0.5306	0.5269	0.3750	0.3770	0.3688	0.3562
PBT	0.4581	0.4701	0.5320	0.5326	0.5131	0.5018	0.3382	0.3442	0.3323	0.3245
HE	0.4028	0.3873	0.4237	0.4334	0.4154	0.4081	0.2956	0.3011	0.2888	0.2845
TA	0.6108	0.5968	0.6300	0.6453	0.6274	0.6263	0.4844	0.4865	0.4716	0.4749
IC	0.6246	0.6172	0.6508	0.6626	0.6477	0.6451	0.5184	0.5129	0.4950	0.5023
BVE	0.4888	0.5824	0.6495	0.6571	0.6400	0.6274	0.3852	0.4132	0.3782	0.3950
R	0.6737	0.6756	0.6951	0.7114	0.6991	0.6940	0.5734	0.6026	0.6070	0.5915
CgbO	0.5918	0.5357	0.5919	0.5839	0.5405	0.5617	0.4689	0.4344	0.4049	0.4204
NCIfOA	0.7458	0.7244	0.7879	0.7870	0.7342	0.7502	0.6343	0.6138	0.5679	0.5895
NCIfIA	1.1020	1.1236	1.1825	1.1829	1.1159	1.1217	1.0832	1.0877	1.0357	1.0442
OD	0.5085	0.5223	0.5534	0.5402	0.5175	0.5347	0.5012	0.4775	0.4446	0.4744
FCFE	0.9653	0.9795	1.0349	1.0547	1.0154	0.9936	0.8850	0.8908	0.8448	0.8484
FCFF	0.8607	0.8277	0.9228	0.8963	0.8306	0.8475	0.7368	0.7285	0.7133	0.6953

Table 5.6…continued

Multiple	PGV									
	TA.Rg		IND		SUP		SEC		SUB	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre	Act	Pre
GP	0.6020	0.6164	0.6438	0.6353	0.6190	0.6292	0.6178	0.6274	0.6299	0.6255
EBITDA	0.4244	0.4668	0.5025	0.4943	0.4835	0.4824	0.4754	0.4789	0.4591	0.4761
EBIT	0.4020	0.4457	0.4657	0.4546	0.4398	0.4441	0.4383	0.4410	0.4249	0.4401
PAT	0.4520	0.4651	0.4308	0.4317	0.4232	0.4221	0.4188	0.4193	0.4199	0.4225
PBT	0.4338	0.4329	0.4209	0.4204	0.4083	0.4093	0.4061	0.4061	0.4065	0.4072
HE	0.3565	0.3672	0.3130	0.3246	0.3140	0.3187	0.3156	0.3169	0.3375	0.3210
TA	0.5630	0.5541	0.6278	0.6072	0.6007	0.5944	0.5753	0.5907	0.5706	0.5855
IC	0.5830	0.5762	0.6526	0.6303	0.6264	0.6179	0.5957	0.6143	0.5937	0.6091
BVE	0.6246	0.5175	0.5770	0.5943	0.5750	0.5748	0.5918	0.5691	0.5824	0.5616
R	0.6824	0.6534	0.6782	0.6501	0.6398	0.6435	0.6316	0.6415	0.6249	0.6418
CgbO	0.4461	0.5026	0.4989	0.5123	0.4984	0.5025	0.4998	0.4996	0.5104	0.4986
NCIfOA	0.6961	0.7043	0.5964	0.6141	0.6144	0.6083	0.6194	0.6065	0.6168	0.6151
NCIfIA	1.2138	1.1802	0.7594	0.7528	0.7777	0.7704	0.7692	0.7753	0.8160	0.8166
OD	0.5119	0.5021	0.5109	0.5413	0.5446	0.5353	0.5358	0.5335	0.5625	0.5297
FCFE	1.0251	1.0039	0.6842	0.6761	0.6802	0.6838	0.6859	0.6860	0.7135	0.7175
FCFF	0.7690	0.8299	0.6056	0.6215	0.6158	0.6224	0.6288	0.6226	0.6509	0.6427

points, as displayed in Figure 5.6, together with the actual data points, are contained in Table 5.6. As is evident, the Actual (Act) and Predicted (Pre) values are very similar. The comparison between the actual and predicted data points over all 16 multiples in Table 5.6 indicates that the loss in data accuracy is negligible. The predictions contained in Table 5.6 can be read from the PCA biplot displayed in Figure 5.6. As is evident from Figure 5.6, projecting all the sample predictions on a biplot would cluster the display and seems nonsensical. However, consider the perpendicular readings of the PGV RoE.Rg, for example, from Figure 5.7.
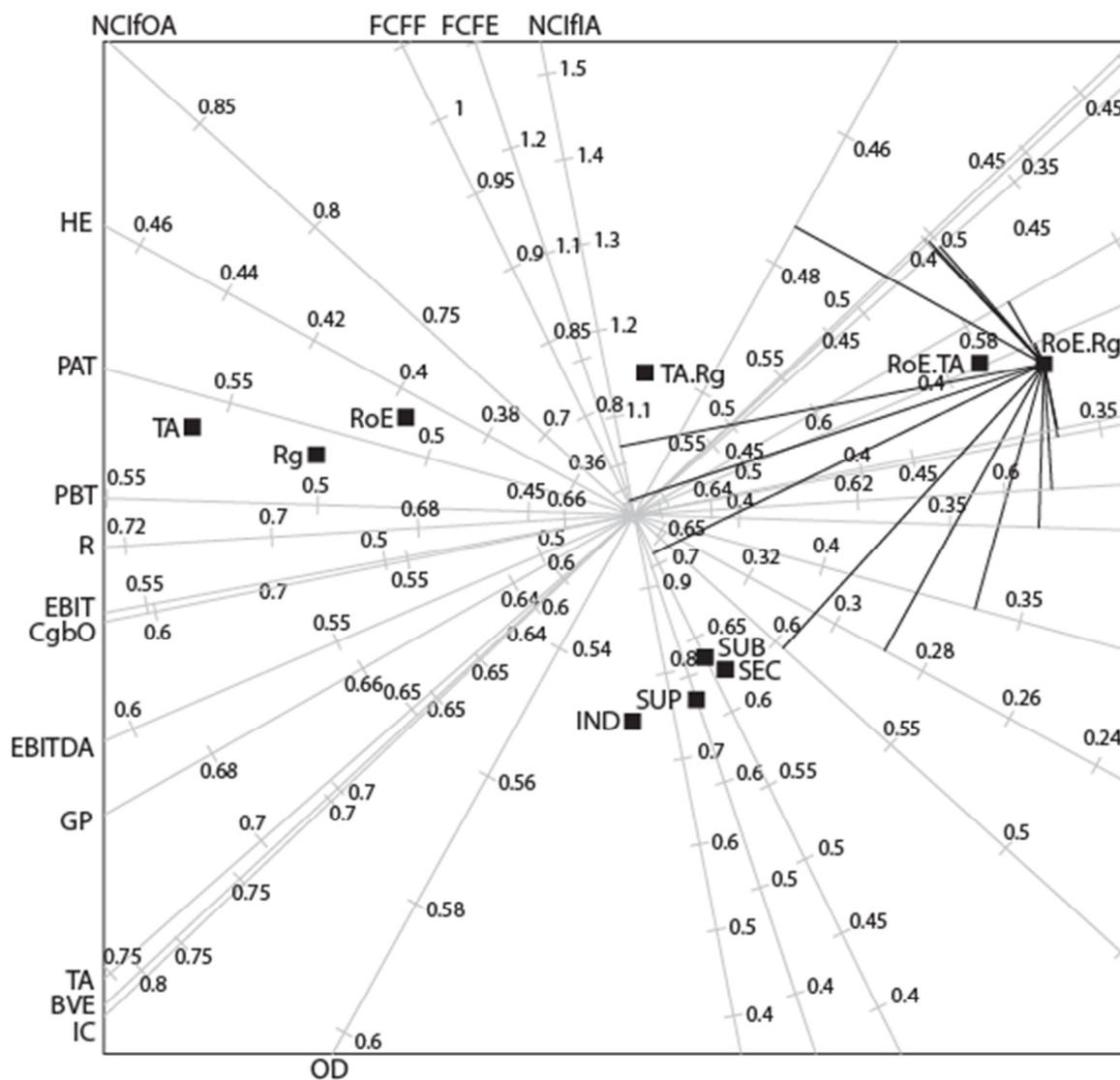
Figure 5.7: PCA biplot of multiples whose peer groups are based on 10 different PGVs (RoE.Rg sample predictions included)

The projection onto the OD axis, for example, indicates a reading somewhere between 0.46 and 0.48, but somewhat closer to 0.48 than to 0.46, which corresponds to the 0.4744 prediction in Table 5.6. Although not shown here, similar readings can be traced to Table 5.6 for all 15 other multiples. If an exact reading from the biplot is required, it can be achieved algebraically.

By default, PCA biplots constructed with *UBBipl*, optimise the relative distances between the positions of the data points and their relationships with the calibrated axes. However, the default setting of the PCA biplots do not optimise the correlations between the calibrated axes, as reflected by the angles between them. Although the angles between these axes are indications of the correlations among the multiples, these angles are not optimised. To gain an accurate display of the correlations, a correlation monoplot is required.

d.   Interpreting correlation monoplots

In order to focus on the correlations between the axes, it is necessary to consider a correlation monoplot, which can be obtained from the *MonoPlot.cor* function in the *R-package UBbipl.* The corresponding correlation monoplot for the data contained in Table 5.4 is depicted in Figure 5.8.

Firstly, note that, as was the case with the PCA biplots, the angles at the origin between the axes represent the correlations among the multiples. In the correlation monoplot these angles are optimally represented, which is not the case with the PCA biplots shown in this dissertation. The length of the arrows reflects the degree of approximation attained in two dimensions, where unit radius reflects a perfect correlation.

As was the case with the PCA biplot in Figure 5.5, smaller angles between the axes reflect higher correlations between the corresponding multiples. Again, for example, the small angles between the asset-based axes confirm their high positive inter-correlations, whereas the almost orthogonal angles between the EBITDA and NCIfIA
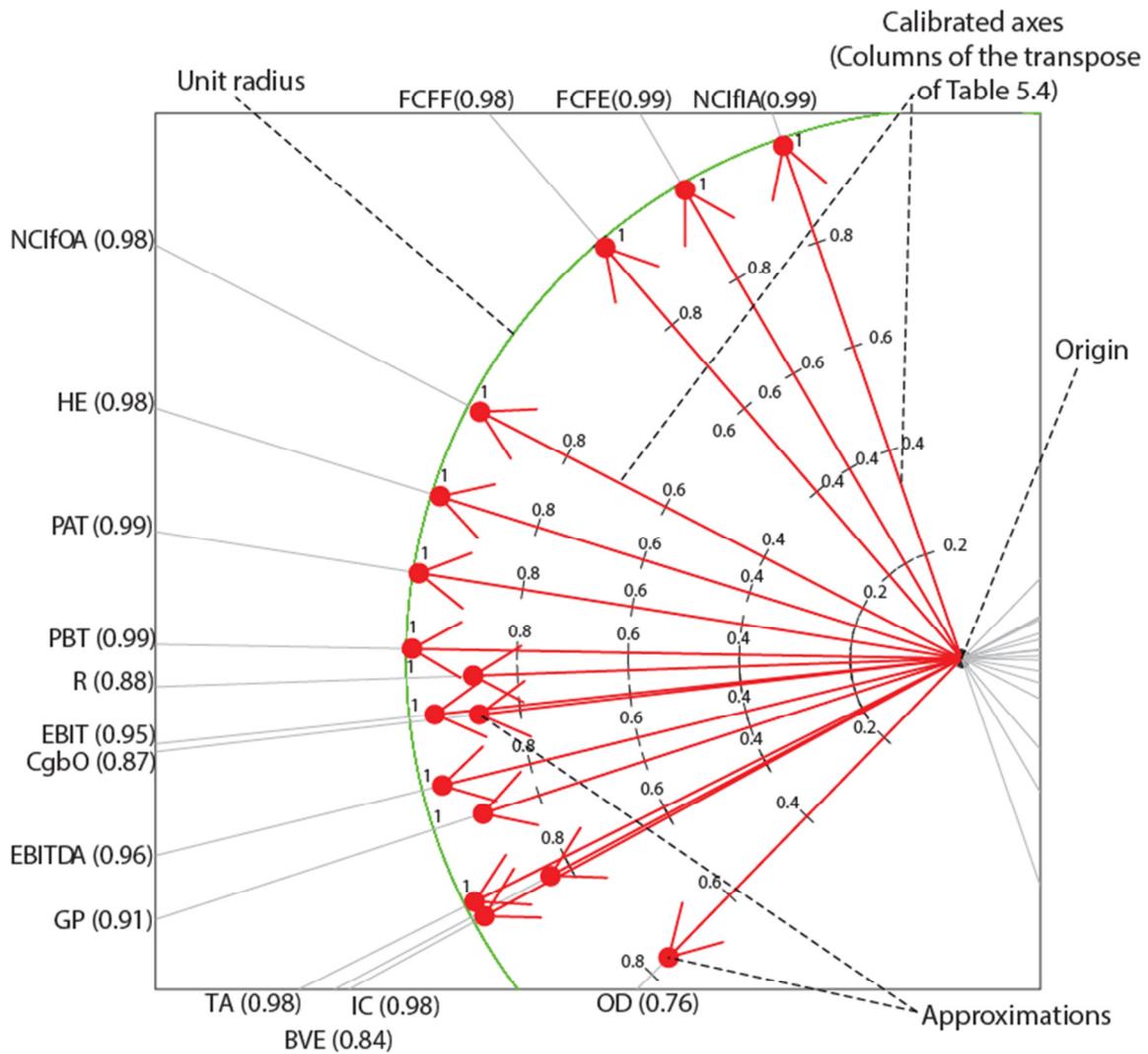
Figure 5.8: Correlation monoplot of multiples whose peer groups are based on 10 different PGVs

axes suggest an almost zero inter-correlation. Note how the correlation monoplot in Figure 5.8 clearly exhibits the opposing directions of the NCIfIA and OD axes. Since the arrows of these two axes point in different directions one can deduce that these two multiples are negatively correlated. While one may be inclined to overlook this occurrence in the PCA biplot in Figure 5.5, it is depicted far more visibly in the correlation monoplot in Figure 5.8, which is why the conventional PCA biplot is useful for analysing the relative positions of the data points, rather than that of the axes.

Secondly, the tips of the red arrows, stretching from the origin along each axis, reflect the degree of approximation of each variable, which is shown numerically in parenthesis next to the label of each axis. Note that, in an exact representation, the

tips of the arrows will be unit distance from the origin, i.e. situated exactly on the green circle, which reflects unit radius. The squared values of these approximations will equate to the predictions as indicated in Table 5.5. The degree of approximation of OD, for example, is indicated as 0.76, the squared value of which is 0.57.[28]

5.5.4.2 Application of the PCA biplot and correlation monoplot

Figure 5.9 depicts a colour-coded version of Figure 5.5. The overall valuation performance depicted in Figure 5.9 suggests that multiples whose peer groups are based on a combination of valuation fundamentals seem to produce more accurate valuations *vis-á-vis* multiples whose peer groups are based on industry classification. However, none of the PGVs consistently produced the most accurate valuations across all 16 multiples. Valuation fundamentals-based multiples produced the most accurate valuations for 81.25% of the multiples, while industry classification-based multiples produced more accurate valuations for 18.75% of the multiples, i.e. the three multiples NCIfIA, FCFE and FCFF. The latter is evident from the colour-coded axes in Figure 5.9, which depict the PGVs that produced the most accurate valuations for each multiple.

However, a distinction should be made among the valuation fundamentals-based peer groups. As discussed in Section 5.5.3, multiples whose peer groups are based on a combination of valuation fundamentals generally produced more accurate valuations than multiples whose peer groups are based on single valuation fundamentals. This is evident from the location of the three single valuation fundamental PGVs, RoE, Rg and TA, relative to two of their combination of valuation fundamentals-based counterparts, RoE.TA and RoE.Rg. Note that, among the combination of valuation fundamentals, TA.Rg produced far less accurate valuations than RoE.TA and RoE.Rg, which is reflected in its location – a significant distance from RoE.TA and RoE.Rg. TA.Rg is the only combination of valuation fundamentals-based peer group that occasionally produced less accurate valuations than one or more of the single valuation fundamentals, as was the case with the NCIfIA multiple, for example.

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[28] For a more detailed discussion on the use of biplots and monoplots see Gower *et al.* (2011).
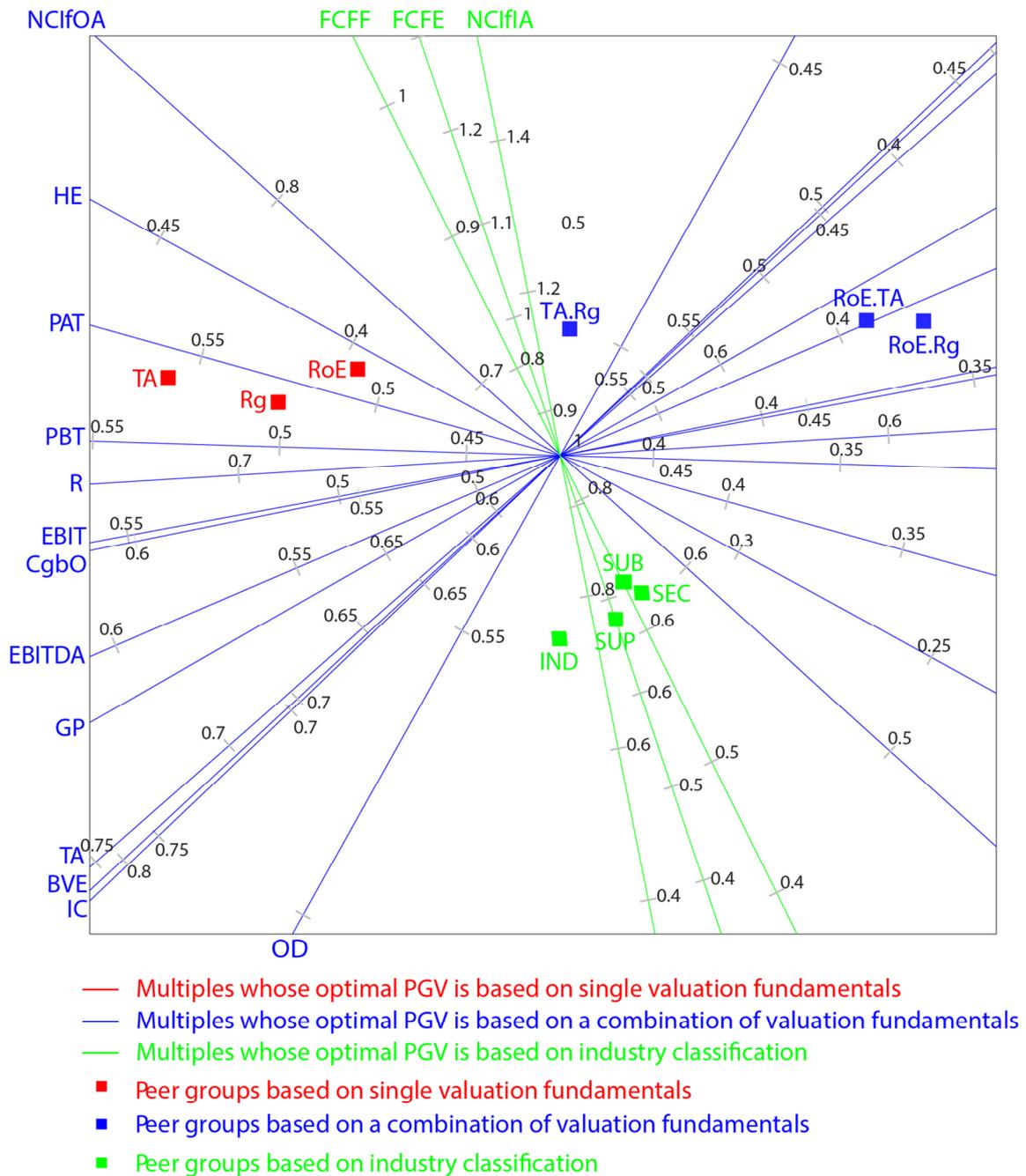
Figure 5.9: PCA biplot of multiples whose peer groups are based on 10 different PGVs (colour-coded)

One should also consider the location of the 10 PGVs relative to the origin. It is evident that single valuation fundamentals generally produced the least accurate results, since they are located the furthest to the left of, and slightly above, the origin. However, single valuation fundamentals occasionally offered a moderate valuation performance by producing valuations that were more accurate than one or more of

the industry-based PGVs. RoE, for example, did so for the BVE multiple.

Industry-based peer groups generally offered a moderate degree of valuation accuracy since they clustered together at the level of the origin. However, three notable exceptions occurred in the case of the multiples NCIfIA, FCFE and FCFF, where the location of the industry-based peer groups were the furthest below the origin, i.e. for these three multiples, they produced the most accurate valuations.

The combination of valuation fundamentals-based peer groups generally offered the highest degree of valuation accuracy, since they were located the furthest to the right of the origin. The exception was TA.Rg, which was located further to the left of RoE.TA and RoE.Rg and closer to the origin, reflecting its generally moderate degree of valuation accuracy.

In order to gain an understanding of the correlations between the 10 PGVs, one has to transpose the data matrix, as contained in Table 5.4. The inter-correlations within and between each of the three PGV categories is depicted in the correlation monoplot in Figure 5.10.

From the degree of approximations (indicated in parenthesis) it is clear that the correlation monoplot approximates the PGVs very well, since they all have values of 0.99 or higher. All 10 PGVs are positively correlated. The inter-correlations between two of the three combinations of valuation fundamentals, namely TA.Rg and RoE.Rg, are particularly highly positively correlated, almost to the extent that they overlap each other. Although RoE.TA is also highly positively correlated with TA.Rg and RoE.Rg, it is positioned at a wider angle from TA.Rg and RoE.Rg. While the inter-correlations between the three single valuation fundamentals are also highly positive, the positive inter-correlations between the industry classification-based PGVs are far weaker.
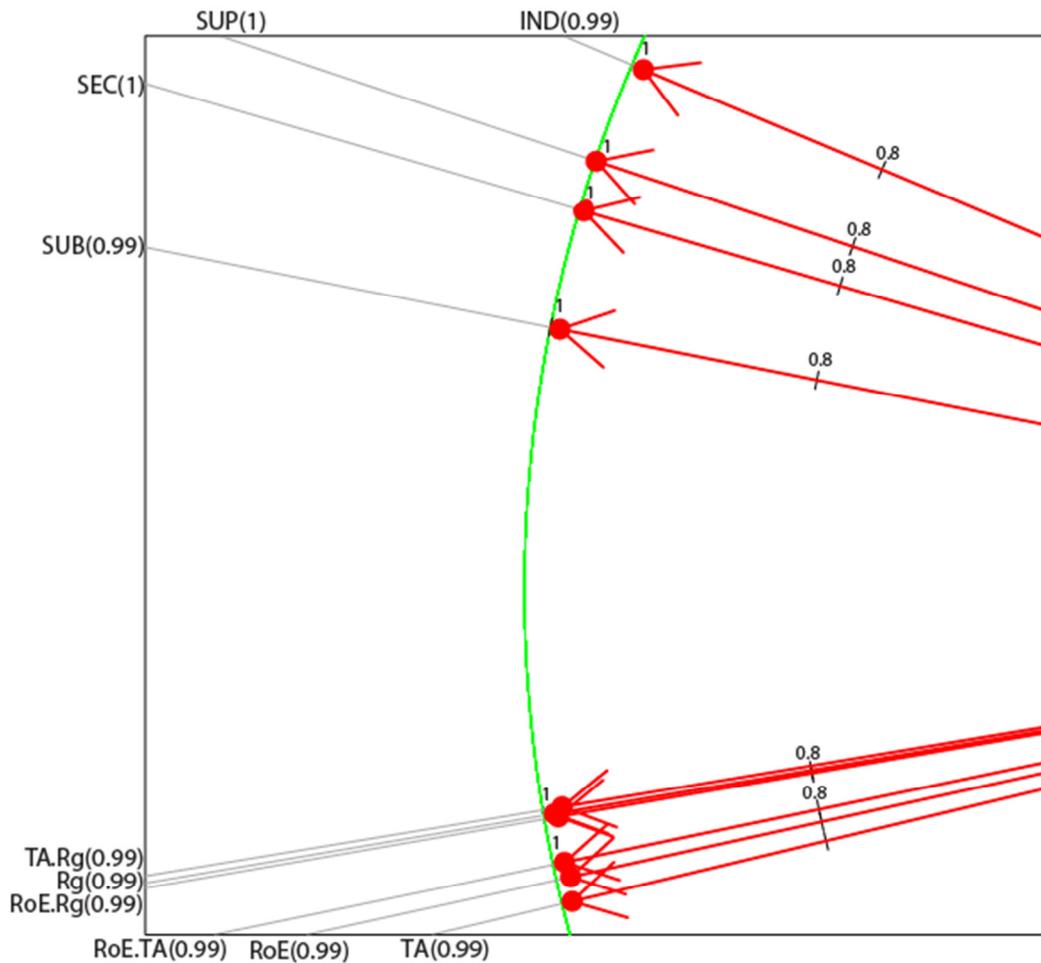
Figure 5.10: Correlation monoplot of 10 different PGVs

Equally evident is the weak positive correlation between the valuation fundamentals-based PGVs and the industry classification-based PGVs. This is in line with the superior valuation performance of the multiples whose peer groups were based on valuation fundamentals, rather than on industry classification.

Chapter 5 offers compelling evidence in favour of a further improvement in peer group selection strategy in comparison with the results obtained from the industry classification-based approach considered in Chapter 4. The evidence suggests that a peer group selection strategy based on a combination of valuation fundamentals, rather than similar industry classifications, or single valuation fundamentals, offers substantial improvements in valuation accuracy.

5.6   CONCLUSION

The objective of Chapter 5 was to investigate whether multiples whose peer groups are based on a combination of valuation fundamentals offer a higher degree of valuation accuracy *vis-à-vis* multiples whose peer groups are based on single valuation fundamentals. The evidence suggests that multiples whose peer group selection is based on a combination of valuation fundamentals offer substantial improvements in valuation accuracy *vis-à-vis* multiples whose peer group selection is based on single valuation fundamentals. Therefore this answers research question two and offers an emerging market reference to peer group selection practices.

The secondary aim was to measure the potential improvement in valuation accuracy that peer group selection based on a careful selection of valuation fundamentals could offer when employing multiples for equity valuation purposes. The research results revealed that a careful selection of valuation fundamentals could offer substantial gains in valuation accuracy. Multiples whose peer groups are based on a careful selection of valuation fundamentals could secure precision gains of as much as 37.88%. On average, multiples whose peer groups were based on a combination of valuation fundamentals offered between 27.14% and 37.88% more accurate valuations than multiples whose peer groups were based on single valuation fundamentals. When considering the valuation performance of individual multiples, the potential for improving the valuation accuracy of multiples is even greater. The P/BVE multiple, for example, indicated a potential increase in valuation accuracy of as much as 71.73%.

The third aim was to determine the optimal valuation fundamental for multiples-based peer group selection purposes. Although RoE and Rg, on average, produced the most accurate valuations among the single valuation fundamentals, offering 7.18% and 2.99% more accurate valuations than TA, respectively, these results were neither consistent nor substantial. The valuation fundamental combination RoE.Rg produced the most accurate equity valuations among the six valuation fundamentals considered in this chapter, offering an increase in valuation accuracy of as much as 37.88%, on average.

The fourth aim was to compare the valuation performance of multiples whose peer groups are based on industry classifications with multiples whose peer groups are based on valuation fundamentals. The evidence suggests that multiples whose peer groups are based on a combination of valuation fundamentals generally perform more accurate valuations than multiples whose peer groups are based on industry classifications. The three multiples offering evidence to the contrary were NCIfIA, FCFE and FCFF.

Therefore, the research results concur with evidence from developed capital markets, which indicates that a combination of profitability and risk or profitability and growth yields the most accurate equity valuations. South African investment practitioners should therefore employ a combination of valuation fundamentals for peer group selection purposes. The evidence also suggests that investment practitioners should take cognisance of the substantial precision gains offered by RoE.TA and RoE.Rg, the latter in particular.

A limitation accompanying these results is that the focus of Chapter 5 was specifically on the valuation performance of multiples-based equity valuations whose peer group selection is based on valuation fundamentals. Although a more comprehensive approach may also incorporate an industry analysis or a combination of three valuation fundamentals, this may be severely hamstrung by a lack of depth in the South African market.

From Chapters 4 and 5 one can, therefore, deduce that, in general, when constructing optimal single factor multiples models, their peer group selection should be based on a combination of valuation fundamentals, provided that there is sufficient data available to accommodate such an approach. Now that the first, and probably most challenging, step towards the construction of optimal single factor multiples models has been completed, one can consider step two. According to the traditional multiples-based valuation approach stipulated in Section 2.6, this entails focusing on the two components of single factor multiples, namely MPVs and value drivers, which can be equity- or entity-based.

CHAPTER 6

THE VALUATION PERFORMANCE OF EQUITY- AND ENTITY-BASED MULTIPLES

6.1   INTRODUCTION

Step two in the construction of single factor multiples requires the scaling of MPVs with corresponding value drivers. Since these two components can be equity- or entity-based, the objective in Chapter 6 is to determine which of the two bases produces the most accurate valuations and, in so doing, to validate H3, which postulates:

H3:   Equity-based multiples models offer higher degrees of valuation accuracy *vis-á-vis* entity-based multiples models.

The intuitive logic behind the superiority of equity-based multiples in terms of valuation accuracy, as postulated above, stems from the design of the investigation in Chapter 6 and capital structure theory. The value drivers that were selected for the investigation in Chapter 6 were based on their suitability from an entity-based perspective, which was a biased approach, i.e. the design of the empirical investigation favoured entity-based multiples. By the same token, capital structure theory favours entity-based multiples over equity-based multiples since the MPVs are, by design, understated.

The secondary aim is to quantify the potential improvement in valuation accuracy that equity-based multiples may offer over entity-based multiples, or *vice versa*. To this end, 16 multiples are constructed from two MPVs, one equity-based and one entity-based, and eight value drivers.

The research results obtained from Chapter 6 add an emerging market perspective to the debate on the valuation precision of equity- and entity-based multiples (Nel *et*

al., 2013b). They are particularly informative to avid proponents of entity-based multiples, such as investment bankers.

6.2   LITERATURE REVIEW

Although the majority of the existing literature tends to focus on either equity- or entity-based multiples, a study by Schreiner and Spremann (2007), which focused on both, found empirical evidence in favour of equity-based multiples. Using the median valuation error as a performance measure, Schreiner and Spremann compared the equity- and corresponding entity-based performance of 16 multiples in the USA equity market. On a comparative basis, their results indicated that equity-based multiples, on average, performed 1.88% more accurate valuations than their entity-based counterparts. Besides the fact that these results seem marginal, equity-based multiples only exhibited a superior valuation performance in 50% of the trailing multiples.

However, Schreiner and Spremann's initial analysis included the valuation performance of forward- and knowledge-related multiples, which resulted in an IMP of 16.12%. For the purpose of comparison with South African data in this study, forward- and knowledge-related multiples were omitted from Schreiner and Spremann's initial analysis, indicating a potential improvement of 1.88%, on average. Forward multiples were omitted since comparative forward multiples are not readily available on South African databases. Knowledge-related multiples, on the other hand, are irrelevant in the South African context as a result of accounting differences between South African and American GAAP.[29]

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[29] Knowledge-related multiples refer to the construction of multiples where adjustments are made to earnings-based value drivers for knowledge-related expenditure, which, in accordance with USA GAAP, is expensed directly in the income statement. Research and development costs, for example, are then regarded as an investment, rather than an expense (Wu, Fargher & Wright, 2010; Damodaran, 2008; Guo, Lev & Shi, 2006; Nelson, 2006; Eberhart, Maxwell & Siddique, 2004; Chan, Lakonishok & Sougiannis, 2001). Based on IAS 38, research costs are expensed in the statement of comprehensive income, but a large portion of development costs are capitalised in the statement of financial position, which makes knowledge-related multiples less relevant in South Africa's case.

Apart from the contribution by Schreiner and Spremann (2007), the international literature on developed markets offers no support for the superiority of equity-based multiples over entity-based multiples, or *vice versa*. The emerging market literature is silent in this regard. In fact, the distinction between equity- and entity-based multiples, it seems, is often neglected by investment practitioners and academics.

PwC (2012) tested the popularity of various multiples in the South African market by surveying the preferences of the top investment practitioners in practice in South Africa. PwC subsequently presented their findings without effectively distinguishing between equity- and entity-based multiples. For example, the top three multiples presented in the PwC report were P/EPS, MVIC/EBITDA and MVIC/EBIT. No explicit distinction was made between the equity and entity bases of these multiples (PwC, 2012).

Similarly, Nel (2009b) tested the valuation performance of primary valuation methods as well as multiples (Nel, 2010; 2009a) in the South African market without explicitly distinguishing between equity- and entity-based multiples. The aim of Chapter 6 is to address the lack of empirical evidence in this regard and to add an emerging market perspective to the existing literature.

6.3   DATA SELECTION

The number of observations was different for each multiple, depending on how well the variables satisfied the criteria stipulated in Section 3.2. As a result, the multiples have different population sizes, varying between 2 470 and 5 292 observations. The total for all the multiples was 35 736 observations for the period 2001 to 2010.

The data were used to calculate 16 multiples, eight equity-based multiples, i.e. multiples where MCap is used as the MPV, and eight entity-based multiples, i.e. multiples where MVIC is used as the MPV. The multiples, i.e. the ratio of the MPVs to the respective value drivers, that were used in the analysis are summarised in Table 6.1.

Table 6.1

Equity- and entity-based multiples

		Value drivers			
		Earnings	**Assets**	**Revenue**	**Cash flow**
MPV	**P or MVIC**	GP	TA	R	CgbO
		EBITDA	IC		FCFF
		EBIT			

There are many potential combinations of MPVs and value drivers that may form part of such an exercise. However, for the purpose of Chapter 6, the focus lies on multiples within each of the four most popular value driver categories, namely earnings, assets, revenue and cash flows (Nel, 2010; PwC, 2010; Nel, 2009a; Liu *et al.*, 2002b; Cheng & McNamara, 2000).

The value drivers were drawn from the statement of comprehensive income (R, GP, EBITDA and EBIT), the statement of financial position (TA and IC) and from the cash flow statement (CgbO and FCFF). As mentioned in Section 2.5.2.1, equity-based value drivers may not be equally apt for entity-based multiples. PAT, PBT, HE, BVE, OD, NCIfOA, NCIfIA and FCFE constitute claims to equity holders, in particular, and are therefore not appropriate value drivers for entity-based multiples. Similarly, when employing entity-based multiples, the denominator should present a claim to all holders on enterprise cash flow and profit (Suozzo *et al.*, 2001). However, to accommodate the empirical testing of the valuation performance of equity-based multiples compared to their entity-based equivalents, the matching requirement is relaxed from an equity-based perspective. Consequently, the value drivers are selected based on their suitability from an entity-based perspective, which seems to be a biased approach, i.e. the design of the empirical investigation seems to favour entity-based multiples.

Similarly, from a theoretical point of view, one could argue that entity-based multiples should outperform equity-based multiples due to the fact that they are less affected by different capital structures among comparable entities (Suozzo *et al.,* 2001).

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However, while MCap is readily available in the market, MVIC is not. As an alternative, MVIC is calculated by adding the book values of preference share capital and debt to MCap, which could generate considerable noise if the circumstances surrounding their issuance have changed considerably (Koller *et al.,* 2005).

6.4   RESEARCH METHODOLOGY

In order to validate H3, one has to compare the ability of equity-based multiples, based on Equation (3.1), and entity-based multiples, based on Equation (3.5), to approximate actual share values. To this end, the target entity's MPV is based on two variables, namely MCap and MVIC. The research methodology that is followed is set out in Section 3.4.1, which culminates in the standardised form of (3.3), where ε_{it} is expressed proportionally to V_{it}^e in Equation (3.4):

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

For the purpose of Chapter 6, peer group selection was based on the McGregor BFA SEC industry classification. SEC was used as the industry classification since previous research from Chapter 4 concluded that refining the industry classification beyond the SEC level added little, if any, value in terms of increased valuation accuracy (Nel *et al.,* 2013a). The evidence from Chapter 5 suggested that multiples whose peer groups are based on a combination of valuation fundamentals offer improvements in valuation accuracy *vis-à-vis* multiples whose peer groups are based on industry classifications. Unfortunately, the evidence from Chapter 5 also indicated that peer group selection based on a combination of valuation fundamentals was accompanied by a substantial decline of between 70% and 80% in N, which hamstrings the application thereof.[30]

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[30]   An equity-entity based comparison was also conducted where the multiples' peer groups were based on a combination of valuation fundamentals. Although not shown here, the analysis rendered similar results, but indicated marginal IMP in valuation accuracy of up to 1.65%, on average, and not consistently so. Unfortunately, the severe loss in data (up to 80%), which results from the lack of depth in the South African market, renders these results less reliable.

The absolute valuation errors of each equity- and entity-based multiple are pooled for all the entity years. The function *CalcVEVds.mpv* was written in *R-code* to implement Equation (3.4). The output of *CalcVEVds.mpv* contained 16 pools of valuation errors (ε_{it}), i.e. two different pools of valuation errors for each of the eight multiples. These ε_{it} were analysed with the use of the *R function AnalyseVE*. This affords one the opportunity to compare the valuation performance of each multiple for which the MPV was equity-based (MCap) and entity-based (MVIC). The performance of the equity- and entity-based multiples is subsequently evaluated by comparing the central tendency and dispersion of their respective valuation errors.

This allows for the construction of an optimisation gap, i.e. a gap that indicates the extent to which equity- or entity-based multiples outperform each other. The optimisation gap indicates the IMP in valuation accuracy that may be secured by employing either an equity-based multiple *vis-á-vis* an equivalent entity-based multiple, or *vice versa*.

6.5   EMPIRICAL RESULTS

The analysis of the equity- and entity-based pools of valuation errors entailed a two-pronged approach. First, the central tendency of the valuation errors in each pool of observations was analysed. This affords one the opportunity to assess the valuation performance of the equity-based multiples in relation to their entity-based equivalents. To this end, the central tendency of the equity-based pool of valuation errors was compared in relation to that of the entity-based pool of valuation errors in order to ascertain which pool contained the smallest cluster of absolute valuation errors. Two measures of central tendency were used to analyse the two pools of valuation errors, namely the mean and the median. Secondly, the dispersion of each pool of valuation errors around these measures of central tendency was analysed. The variation of the observations in each cluster of valuation errors was compared in order to determine which pool of valuation errors contained the narrowest dispersion of data. Five measures of dispersion were used for this purpose, namely the SD, CV, IQR, MAD and the CMAD. This affords one the opportunity to assess the relative size of the dispersion of observations in each pool of valuation errors.

6.5.1   Descriptive statistics: Central tendency

Following the application of the equity- ($\hat{\lambda}_{pt}^{e}$) and entity-based ($\hat{\lambda}_{pt}^{n}$) multiple estimates to the eight respective value drivers, the valuation performance of the equity- and entity-based pools of valuation errors (ε_{it}) was analysed. The results concerning the differences in central tendency of the two pools of valuation errors are illustrated in Figures 6.1 and 6.2.[31] The eight value drivers depicted in these boxplots are ranked according to their relative valuation performance, based on their mean (Figure 6.1) and median (Figure 6.2) absolute valuation errors. The value drivers are therefore ranked from those reflecting the highest increase in valuation accuracy, when substituting entity-based multiples with their equity-based counterparts, to those reflecting the lowest increase in valuation accuracy. The percentages in parenthesis indicate the mean- (Figure 6.1) and median- (Figure 6.2) based IMP in valuation accuracy that may be secured when substituting entity-based multiples with their corresponding equity-based multiples.

As is evident from Figure 6.1, all equity-based multiples indicate lower mean valuation errors (depicted as asterisks) than their corresponding entity-based counterparts, i.e. equity-based multiples perform more accurate valuations than their entity-based counterparts. However, in order to accommodate the outliers, the scaling of the boxes in Figure 6.1 was reduced considerably, which, apart from the mean observation, inhibits a more detailed analysis, particularly of the central 50% of the observations (the boxes). A more detailed analysis of the box area requires the demarcation of a limited range for the boxplots. Subsequently, in Figure 6.2, the scaling is adjusted to accommodate a more detailed analysis of the boxes. The zoomed illustration in Figure 6.2 indicates that all the equity-based multiples indicate lower median valuation errors (depicted as white horizontal lines in the boxes) than their corresponding entity-based counterparts, i.e. equity-based multiples perform more accurate valuations than their entity-based counterparts.

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[31]   The notches in the boxplots in Figure 6.1 and Figure 6.2 indicate approximate 95% confidence levels for the respective medians, which allow statistical inference.

In addition, two important observations are evident when comparing Figure 6.1 and Figure 6.2. Firstly, all the median valuation errors in Figure 6.1 are lower than their corresponding mean-based valuation errors, which is the case for all eight value drivers. Secondly, as is evident from Figures 6.1 and 6.2, the IMPs of the median valuation errors are smaller than the corresponding IMPs of the mean-based valuation errors. The reason for both these observations can be traced to the fact that the mean is far more susceptible to outliers than the median, which also explains why the ranking of the mean valuation errors in Figure 6.1 is different to the ranking of the median valuation errors in Figure 6.2. Note the number and magnitude of the outliers above the top whiskers in Figure 6.1.[32] These outliers naturally affect the measures of central tendency, such as the mean, which is one of the primary reasons that researchers prefer measures such as the median above the mean (Bhojraj & Lee, 2002; Liu *et al.*, 2002b; Beatty *et al.*, 1999). Aside from the influence of the outliers, the data do not exhibit a normal distribution pattern. All 16 boxes in Figure 6.1 are located significantly closer to the smallest non-outliers than to the largest non-outliers, which indicate that the data are positively skewed.

From Figure 6.2, it is evident that the IQRs narrow as entity-based multiples are substituted with their corresponding equity-based multiples. Although the boxplots in Figure 6.2 indicate that the lower boundary (P25) and the upper boundary (P75) of the boxes decline as entity-based multiples are substituted for equity-based multiples, the decline in the upper boundary is far more substantial than that of the lower boundary. All eight value drivers that were tested demonstrated this tendency. In addition, the median valuation errors of both the upper 50% of observations and the bottom 50% of observations decreased when entity-based multiples were substituted with equity-based multiples. The latter is in line with the median valuation error of the pooled observations, which also decreased when substituting entity-based multiples with their equity-based counterparts.

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[32] The interval parameters for the top and bottom whiskers in Figure 6.1 are [P75 + 5 (P75 - P25); P25 - 5 (P75 - P25)]. The observations located outside these interval parameters are flagged as outliers. Note that the outliers occur only above the top whiskers in Figure 6.1.
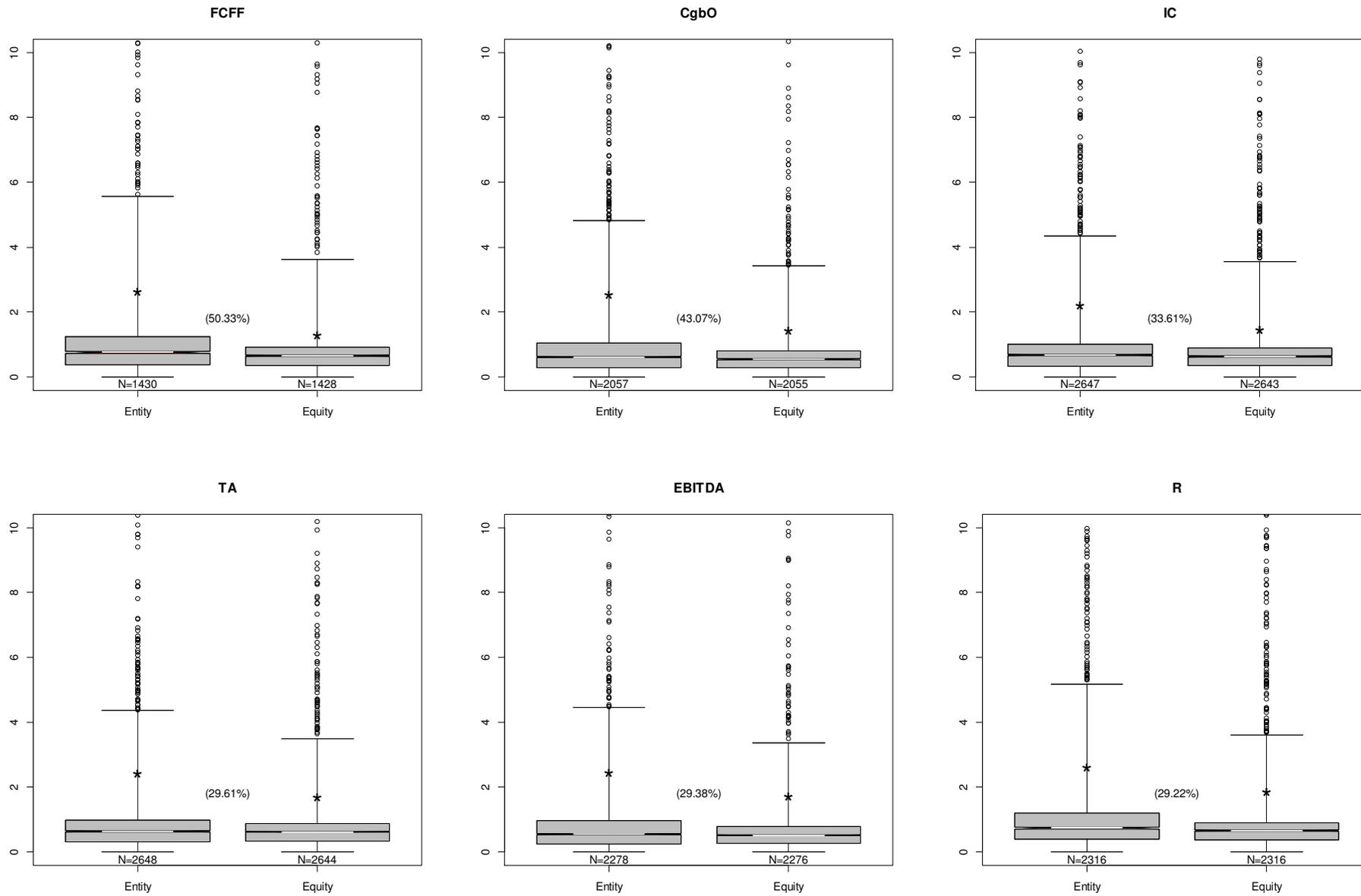
Figure 6.1: Mean-based absolute valuation errors: Entity- versus equity-based multiples (complete range)
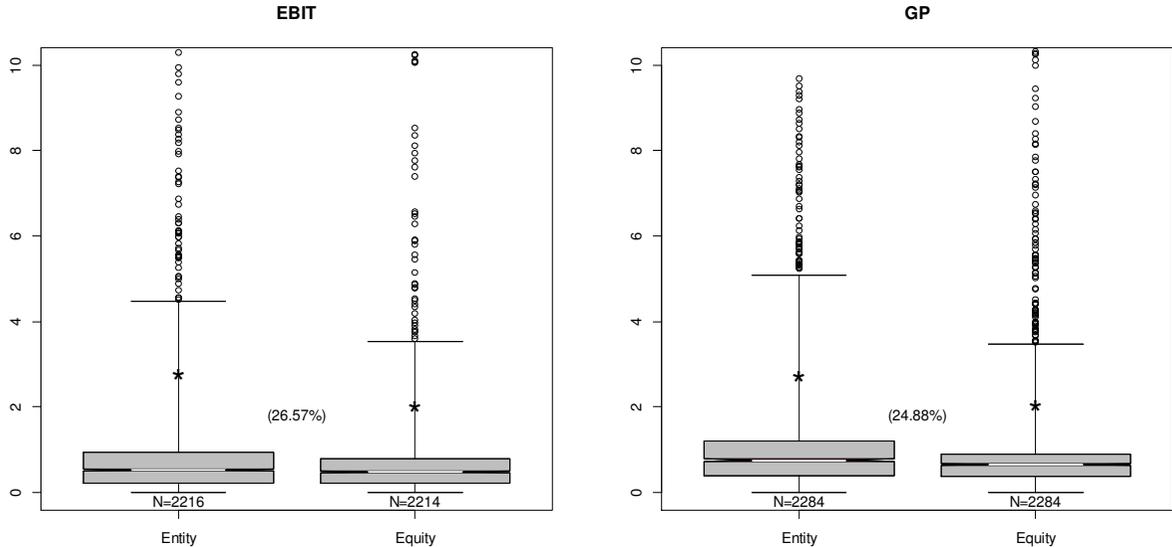
Figure 6.1…continued
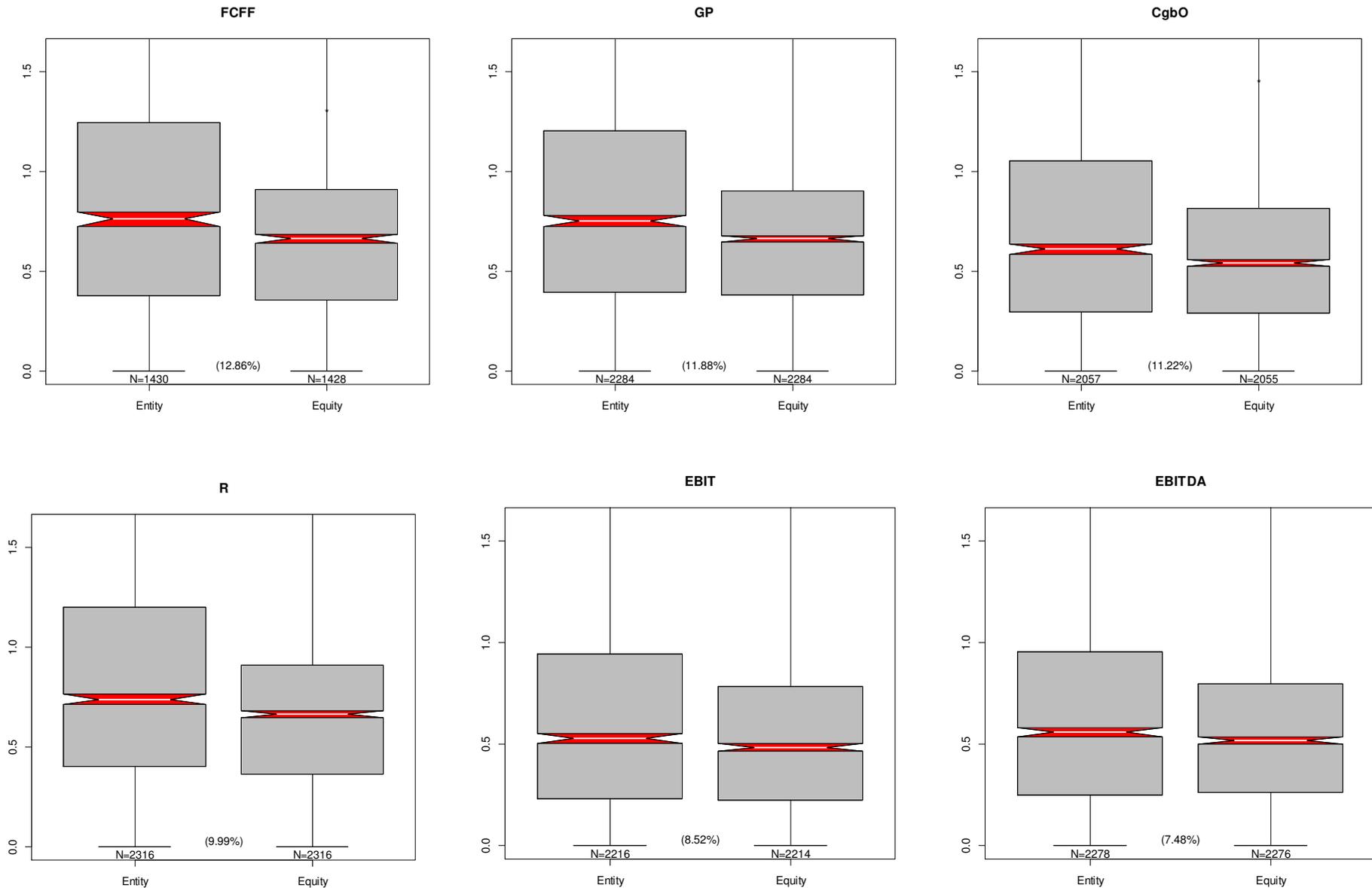
Figure 6.2: Median-based absolute valuation errors: Entity- versus equity-based multiples (limited range focusing on the central 50% of the observations, i.e. the boxes)
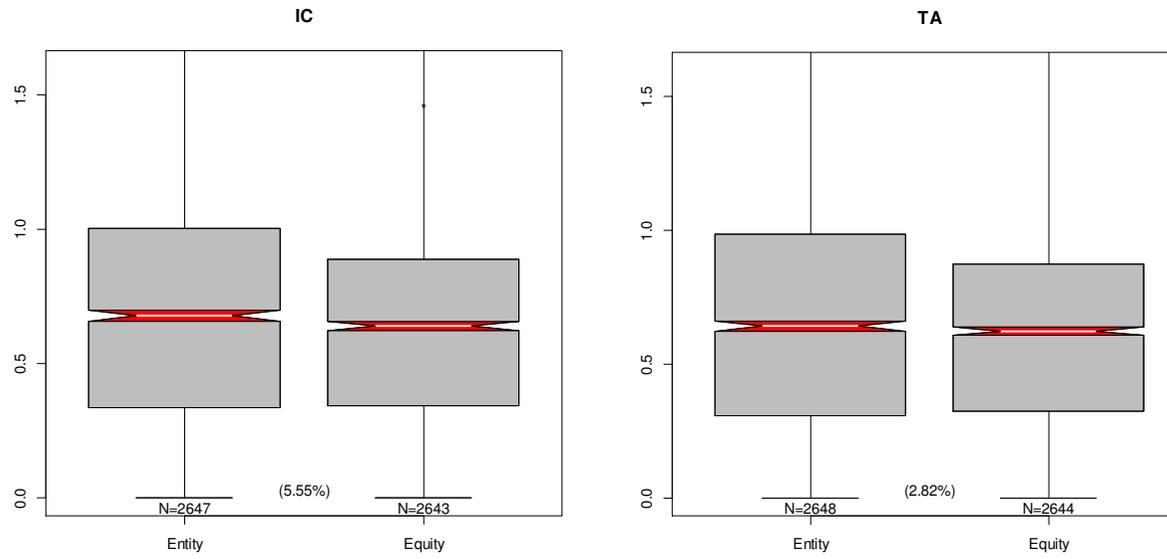
Figure 6.2…continued

The superiority of equity-based multiples is also evident from the radar graphs in Figure 6.3, which present a comparative overview of the central tendency-based valuation performance of equivalent equity- and entity-based multiples, i.e. multiples with similar value drivers. Although the scaling of the mean and median in Figure 6.3 is different, this is largely irrelevant for the purpose of the analysis, since the emphasis is on the relative performance of equity- and entity-based multiples. The two measures of central tendency that were employed in the analysis, namely the mean and the median, rendered similar results. The mean and median radar graphs in Figure 6.3 illustrate that equity-based multiples produce more accurate valuations than their entity-based equivalents, i.e. equity-based multiples have smaller valuation errors than their entity-based equivalents.

The mean indicates a consistent improvement across all the value drivers when substituting entity-based multiples with their equity-based equivalents. In Table 6.2 the overall mean-based IMP range is indicated as 24.88% to 50.33%, with P/GP showing the least substantial IMP and P/FCFF showing the most substantial IMP. However, a comparison of the means, although widely used in statistical analysis, should be approached with the necessary caution. The means were inflated by the outliers, which were particularly prevalent in this study, as can be gleaned from the number of bubbles in Figure 6.1. The mean's susceptibility to outliers, together with the fact that the data are positively skewed, necessitated the use of a different measure of central tendency, such as the median, which is a more robust measure of central tendency.

The median valuation errors in Figure 6.2 and Table 6.2 indicate a consistent improvement across all the value drivers when substituting entity-based multiples with their equity-based equivalents. The overall median-based IMP range indicated in Figure 6.2 and Table 6.2 is 2.82% to 12.86%, with P/TA showing the least substantial IMP and P/FCFF showing the most substantial IMP. However, the boxplots in Figure 6.2 indicate that 50% of the notches overlap; and only marginally so, when substituting entity-based multiples with their equity-based counterparts.
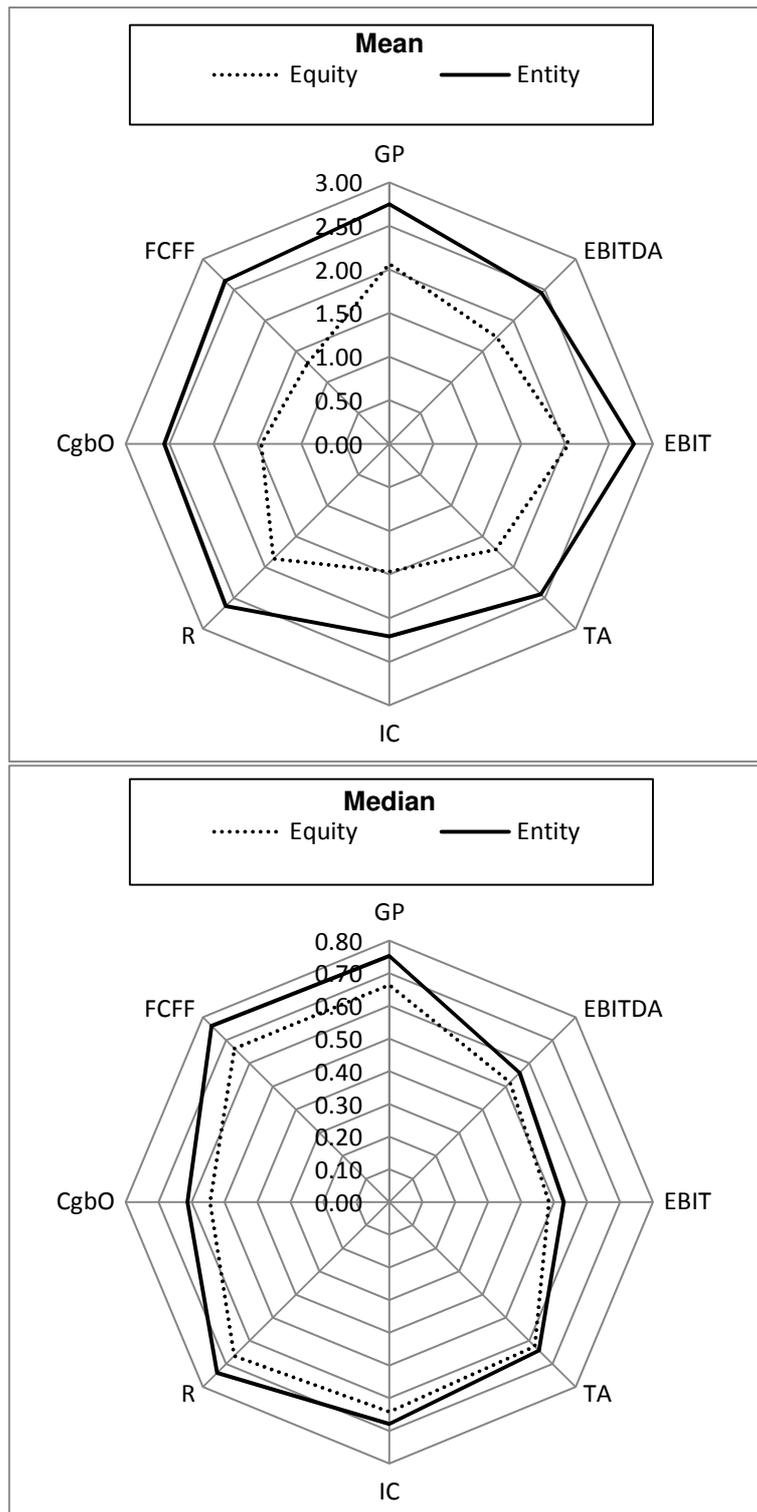
Figure 6.3: Central tendency of the absolute valuation errors of equity- and entity-based multiples

Consequently, 50% of the multiples offered statistically significant improvements of the median at the 95% confidence level. The four multiples that offer improvements of statistical significance are P/FCFF, P/GP, P/CgbO and P/R. As is evident from the

Table 6.2

Optimisation gap: Substituting entity- with equity-based multiples

		Central tendency		Dispersion				
					IMP			
	N	**Mean**	**Median**	**SD**	**CV**	**IQR**	**MAD**	**CMAD**
Equity versus Entity	**41 582**	**32.49%**	**9.82%**	**33.50%**	**4.64%**	**30.76%**	**28.01%**	**20.37%**
P/GP vs MVIC/GP	4 568	24.88%	11.88%	15.88%	-11.97%	35.57%	31.90%	22.72%
P/EBITDA vs MVIC/EBITDA	4 554	29.38%	7.48%	22.57%	-9.63%	24.39%	20.26%	13.81%
P/EBIT vs MVIC/EBIT	4 430	26.57%	8.52%	11.71%	-20.22%	21.41%	16.77%	9.03%
P/TA vs MVIC/TA	5 292	29.61%	2.82%	29.94%	0.46%	18.78%	18.44%	16.07%
P/IC vs MVIC/IC	5 290	33.61%	5.55%	52.17%	27.95%	18.12%	18.20%	13.39%
P/R vs MVIC/R	4 632	29.22%	9.99%	16.17%	-18.44%	31.44%	27.59%	19.55%
P/CgbO vs MVIC/CgbO	4 112	43.07%	11.22%	42.01%	-1.87%	30.31%	27.55%	18.40%
P/FCFF vs MVIC/FCFF	2 858	50.33%	12.86%	81.26%	62.28%	36.17%	33.35%	23.51%
Min		24.88%	2.82%	11.71%	-20.22%	18.12%	16.77%	9.03%
Max		50.33%	12.86%	81.26%	62.28%	36.17%	33.35%	23.51%

IMP - Potential percentage improvement; N - Number of observations; SD - Standard Deviation; MAD - Median Absolute Deviation; IQR - Interquartile Range; CV - Coefficient of Variation; CMAD - Coefficient of MAD; Min - Minimum; Max - Maximum; P - Market Price per share; MVIC - Market Value of Invested Capital; GP - Gross Profit; EBITDA - Earnings Before Interest, Tax, Depreciation and Amortisation; EBIT - Earnings Before Interest and Tax; TA - Total Assets; IC - Invested Capital; R - Revenue; CgbO - Cash generated by Operations; FCFF - Free Cash Flow to the Firm

two measures of central tendency, the median offers a more conservative IMP range relative to the mean. As mentioned earlier, the median is a more robust measure of central tendency, since it is less susceptible to the impact of outliers.

The extent to which the mean and the median can be regarded as accurate representatives of the pools of valuation errors will also depend on the variation contained in each pool of valuation errors. While the mean and the median reflect the central tendency of the valuation errors, they fail to describe the dispersion of the valuation errors. An equity-based pool of valuation errors, for example, may have a similar mean to that of its entity-based counterpart, while the dispersion in their respective pools of valuation errors may be vastly different. Consequently, it is of equal importance to analyse the dispersion of the opposing pools of valuation errors in order to understand how the data clusters around the mean and the median.

6.5.2   Descriptive statistics: Dispersion

The radar graphs in Figure 6.4 depict the relative degree of dispersion between the equity- and entity-based multiples, as measured by the SD and the CV. Of particular importance is the dispersion of the valuation errors around the mean, as measured by the CV. The CV affords one the opportunity to compare the degree of variability between the various equity- and entity-based pools of valuation errors.

As is evident from Figure 6.4, the CV renders inconsistent results, i.e. equity-based multiples do not offer consistently more accurate valuations than their entity-based counterparts, which is reflected in the IMP range of -20.22% to 62.28% in Table 6.2. In addition, only 25% of the value drivers indicate that equity-based multiples exhibit less variability than their entity-based counterparts. The contradiction and inconsistency of the CV results can be traced to the susceptibility of the SD and the mean to outliers. Consequently, the results of the mean, SD and the CV may be misleading, prompting researchers generally to revert to an analysis of the median and the dispersion around it.
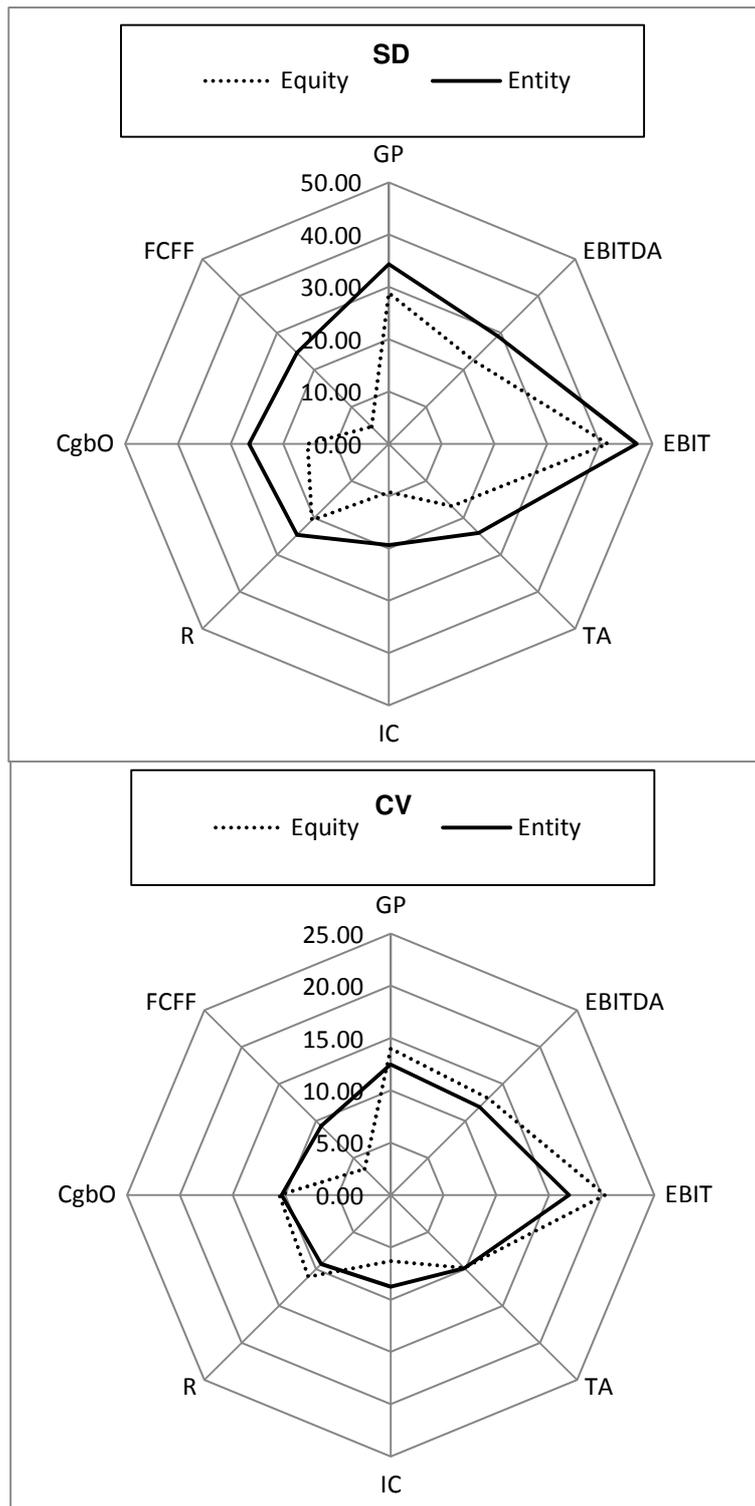
Figure 6.4: Variability of absolute valuation errors around the mean: Scale of ε_{it} **(SD) and fraction of the mean (CV)**

The IQR and the MAD are generally regarded as more robust measures of dispersion. The IQR calculation, however, is based on only two values (P75 and P25), while the MAD is based on all observations, which renders it more reliable. In

addition to equity-based multiples displaying smaller valuation errors than their entity-based counterparts (as is evident from Figure 6.3), the IQR and the MAD (as depicted in Figure 6.5) indicate that equity-based multiples exhibit less variation than their entity-based counterparts. The IQR and MAD display a similar range of IMP across all eight value drivers. From Table 6.2, it is evident that the IQR has an IMP range of 18.12% to 36.17%, with P/IC exhibiting the least substantial IMP and P/FCFF exhibiting the most substantial IMP, while the MAD reflects an IMP range of 16.77% to 33.35%, with P/EBIT exhibiting the least substantial IMP and P/FCFF showing the most substantial IMP.

The relative dispersion of the valuation errors around the median is measured by the CMAD, which is a more robust alternative to the CV. Contrary to the CV, which, as illustrated in Figure 6.4, rendered inconsistent results, the CMAD indicated that, for all the value drivers concerned, equity-based multiples exhibit less variability relative to the respective medians than their entity-based counterparts. From Table 6.2, it is evident that the CMAD IMP range was 9.03% to 23.51%, with P/EBIT showing the least substantial IMP and P/FCFF showing the most substantial IMP.

Table 6.2 contains a summary of the relative performance of the equity-based multiples *vis-á-vis* entity-based multiples, for the construction of an optimisation gap. The optimisation gap indicates the IMP in valuation accuracy that may be secured by substituting the least accurate multiple (multiple with the largest valuation error (ε_{it})) with the most accurate multiple (multiple with the smallest valuation error (ε_{it})).

Contrary to the initial analysis in Figure 6.1 and Figure 6.2, where the emphasis was on the smallest valuation error, the focus in Table 6.2 is on the highest IMP in valuation accuracy. Consequently, the positive percentages in Table 6.2 indicate, for each of the two measures of valuation error central tendency and the five measures of valuation error dispersion, to what extent equity-based multiples outperform entity-based multiples. For example, by employing P/GP instead of MVIC/GP, the median-based valuation accuracy of the multiples can be improved by 11.88%, which is far more conservative than the corresponding values found when using the mean.
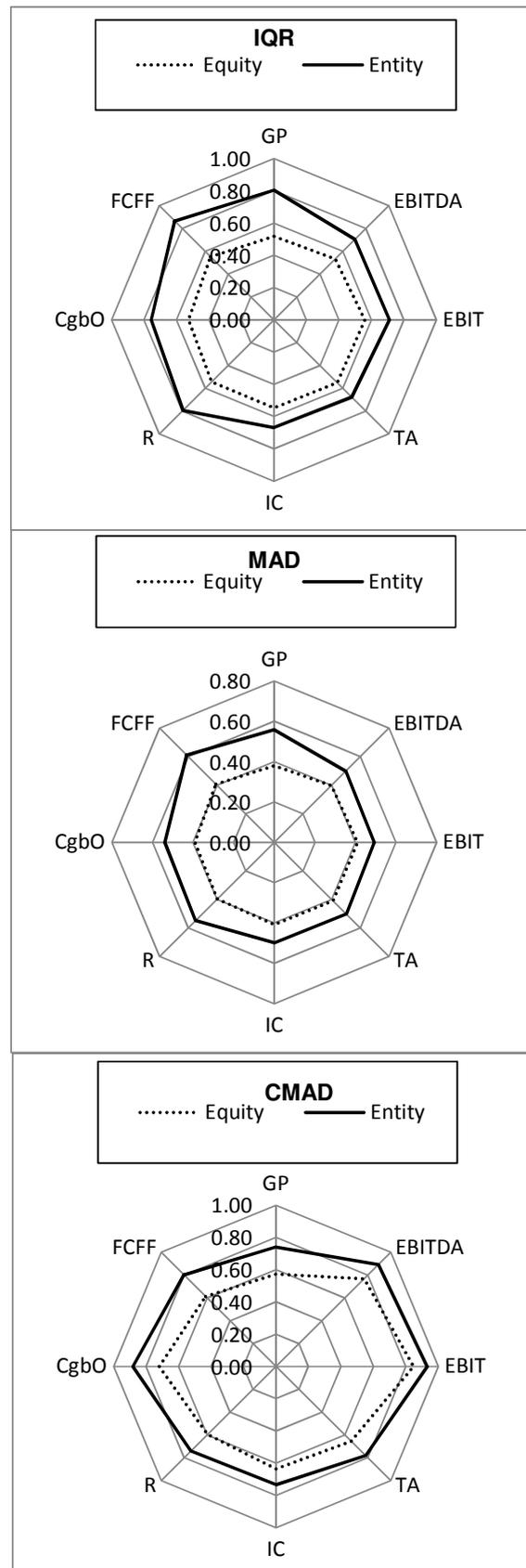
Figure 6.5: Variability of absolute valuation errors around the median: Scale of

ε_{it} **(IQR and MAD) and fraction of the median (CMAD)**

Conversely, negative percentages indicate the extent to which entity-based multiples outperform equity-based multiples. The overall median-based IMP range is between 2.82% and 12.86%, which compares remarkably well with the evidence from the developed market of the USA, for example, where a comparative IMP was measured at between 3.87% and 16.36% (Schreiner & Spremann, 2007).

This improvement in the measures of central tendency, together with the improvement in the dispersion about the median as found by the MAD or CMAD, suggests that equity-based multiples produce more accurate valuations than entity-based multiples. That is, equity-based multiples consistently offer superior explanatory power of market values *vis-á-vis* entity-based multiples for six of the seven measures of central tendency and dispersion. Although the consistency of this observation is somewhat obscured by the results of the CV, one needs to take cognisance of the fact that the mean, the SD and the CV are unduly influenced by outliers, which were rather prevalent in this study.

The evidence is overwhelmingly stacked in favour of the explanatory power of equity-based multiples *vis-á-vis* entity-based multiples, i.e. equity-based multiples explain market values more accurately than their entity-based counterparts. This is confirmed by the fact that the equity-based median valuation errors of all eight value drivers consistently offered more accurate results than their entity-based counterparts. In addition, an analysis of the dispersion of the valuation errors indicated that equity-based multiples display a smaller degree of variability than their entity-based counterparts. Equity-based multiples consistently outperformed entity-based multiples for the median as a measure of central tendency and for the MAD and the CMAD as measures of dispersion for all eight value drivers that were tested.

These results gain increased significance if one considers that the multiples that were selected for this study were based on entity-based value drivers. One may therefore be inclined to argue that the design of the study was biased in favour of entity-based multiples. Similarly, valuation theory suggests that entity-based multiples offer various benefits over equity-based multiples, which also favours entity-based multiples. However, despite these biases, equity-based multiples produced more accurate valuations than their entity-based counterparts.

The reason offered by the literature for the superior valuation performance of equity-based multiples is that noise, which is caused when the book values of preference share capital and debt, particularly the latter, are used as proxies for their respective market values in the estimation of the entity value, distorts the accuracy of entity-based multiples (Schreiner & Spremann, 2007; Koller e*t al.,* 2005; Sweeney, Warga & Winters, 1997). The empirical evidence in this study suggests that the noise is considerable, especially if one considers that valuation theory and the design of this study were biased in favour of entity-based multiples.

6.6   CONCLUSION

The objective of Chapter 6 was to investigate whether equity- or entity-based multiples perform the most accurate equity valuations. As such, the evidence presented an emerging market perspective in this regard. Despite the bias of the design of the study, and valuation theory favouring entity-based multiples, equity-based multiples consistently produced more accurate valuations in terms of size and dispersion of valuation errors, than their entity-based counterparts. The superiority of equity-based multiples was confirmed by all the multiples selected. Therefore, the research results verified H3, in that equity-based multiples explain market values better than entity-based multiples, which is in line with empirical evidence from developed capital markets. This is confirmed by the fact that the median valuation errors of all eight value drivers indicated that equity-based multiples offered consistently more accurate valuations than their entity-based counterparts. In addition, an analysis of the dispersion of the valuation errors indicated that equity-based multiples display a smaller degree of variability than their entity-based counterparts. Equity-based multiples outperformed entity-based multiples for both measures of dispersion, namely the MAD and the CMAD.

The secondary aim was to quantify the potential improvement in valuation accuracy that equity-based multiples may offer over entity-based multiples, or *vice versa*. By comparing the valuation performance of equity-based multiples with that of entity-based multiples, it was evident that the substitution of an entity-based multiple with its corresponding equity-based counterpart can improve the overall accuracy of

individual valuations by between 2.82% and 12.86%, based on the median valuation error, which is a conservative estimate. One should take cognisance of the fact that this study, in particular the selection of value drivers, was designed from an entity perspective, which may have suppressed the magnitude of the results. From a dispersion perspective, the improvement ranges in valuation accuracy based on the MAD and the CMAD were 16.77% to 33.35% and 9.03% to 23.51%, respectively.

The results therefore confirm the superiority of equity-based multiples *vis-á-vis* entity-based multiples and present an answer to research question three. Why do equity-based multiples outperform entity-based multiples? The only plausible explanation for the sub-optimal performance of entity-based multiples is that noise, which is caused when the book values of preference share capital and debt are used as proxies for their respective market values in the estimation of the entity value, distorts the accuracy of entity-based multiples. Based on the empirical evidence contained in this study, one must deduce that the noise is considerable, especially if one considers that valuation theory and the design of this study were biased in favour of entity-based multiples.

What are the practical implications of these results? Investment practitioners may be inclined to prefer equity- or entity-based multiples, depending on their specific circumstances and objectives. However, the evidence suggests that equity-based multiples are superior to entity-based multiples and should therefore constitute best practice *per se.*

In Chapter 6 it has, therefore, been established that the optimal MPV is equity-based. The next step in the construction of optimal single factor multiples is the identification of optimal value drivers with which to scale the equity-based MPV. Consequently, the valuation accuracy of value drivers is investigated in Chapter 7.

CHAPTER 7

THE VALUATION PERFORMANCE OF VALUE DRIVERS

7.1   INTRODUCTION

In order to complete step two of the traditional multiples valuation approach it is necessary to determine which value drivers are best suited for the purpose of scaling P. Consequently, the focus in Chapter 7 is on the valuation performance of the 16 value drivers contained in Table 2.1 for the period 2001 to 2010.[33] The objective is to assess the valuation performance of multiples that are constructed based on each of the 16 value drivers. This investigation will afford one the opportunity to compare the precision of individual multiples stemming from the five value driver categories, namely earnings, assets, revenue, dividends and cash flows and, in so doing, to validate H4, which postulates:

H4:   Multiples models that are constructed on earnings-based value drivers offer higher degrees of valuation accuracy *vis-á-vis* multiples models that are constructed on asset-, revenue-, dividend- and cash flow-based value drivers.

The popularity of earnings-based value drivers among investment practitioners, compared to the other value drivers, suggests that they have the ability to produce more accurate valuations. Although evidence from the international finance literature seems to confirm the latter, no such evidence exists in emerging markets such as South Africa.

Therefore, in order to validate H4, the analysis adopts a three-pronged approach. The modelled valuations are compared to the market on an inter- and intra-value driver category basis, as well as on an individual value driver basis. The secondary

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[33]   Given that the superiority of equity-based multiples was confirmed in Chapter 6, one could have discarded the entity-based value drivers from Chapter 7 onwards. However, for comparative purposes, all 16 value drivers were included in the analyses in Chapters 7 and 8.

aim is to quantify the opportunity cost of a sub-optimal choice of value driver and to rank the value drivers according to their valuation performance in this regard. Thirdly, the mispricing tendencies of multiples-based modelling is investigated, i.e. the tendency of the constructed multiples to over- or undervalue the share prices on the JSE. Biplots, based on PCA, are employed to investigate the consistency of these rankings over time.

The research results obtained from Chapter 7 offer an emerging market perspective on the valuation precision of 16 value drivers and should be of particular interest to investment practitioners who are stern supporters of the use of EBITDA- and EBIT-based multiples. Equally informative was the bias tendencies that emerged from the analysis. This should prove insightful to investment practitioners who opt to apply ex-model adjustments to multiples, which is a common phenomenon in practice (PwC, 2012; Harrington, 2004).

7.2   LITERATURE REVIEW

Although limited empirical studies exist on multiples in emerging markets, a number of researchers have conducted empirical research on value drivers in developed markets. The findings support investment practitioners' preference for earnings-based multiples (Rappaport & Mauboussin, 2001), since most researchers conclude that earnings-based multiples are superior to their counterparts. The latter explains why Liu *et al.* (2002b) found earnings to be the best value driver in valuing equity. They focused on equity-based multiples and investigated which value drivers performed the best amongst earnings, cash flows, dividends and revenue, to approximate stock prices in 10 countries between 1987 and 2001. However, Liu *et al.* (2002b) neglected to test for asset-based value drivers and limited the study to just four value drivers. They found that multiples based on earnings generally performed the best valuations, while those based on cash flow and dividends produced average results. Multiples based on revenue performed the worst. In a study of the valuation accuracy of the P/EPS and the P/BVE ratios as benchmarks between 1973 and 1992, Cheng and McNamara (2000) found similar results, i.e.

earnings was the most important value driver. Herrmann and Richter (2003) and Abukari, Jog and McConomy (2000) drew similar conclusions.

However, some of these studies tend to include a limited number of value drivers, which, if regarded as representative of entire value driver categories, may suggest a biased approach. Herrmann and Richter (2003), for example, tested the valuation performance of only five value drivers, namely E; earnings before interest; earnings before interest, depreciation and amortisation; BVE and IC. Similarly, Liu *et al.* (2002b) investigated the valuation performance of only four value drivers and neglected to include an asset-based value driver, while Cheng and McNamara (2000) compared the valuation performance of only two value drivers.

While some of these studies have extended their selection of value drivers, they tend to cover only a limited number of entity years. Herrmann and Richter (2003), for example, test the valuation performance of five value drivers over the three-year period 1997 to 1999 and Abukari *et al.* (2000), although including a wider selection of value drivers, only cover the five-year period 1992 to 1996.

A number of researchers have refined their research to accommodate an intra-value driver category performance analysis. Most of these studies focused on earnings as a value driver category. Baker and Ruback (1999) compared EBITDA, EBIT and R as value drivers and found that industry-adjusted EBITDA outperformed EBIT and R. Lie and Lie (2002) came to the same conclusion, finding EBITDA to be a more accurate value driver than EBIT, and that forward multiples outperformed historical multiples. Schreiner and Spremann (2007) investigated the valuation performance of R, GP, EBITDA, EBIT, EBT and E, and found somewhat different results. Their results indicated that, with the exception of R and GP, which are located higher up in the statement of comprehensive income, EBITDA performed the least accurate equity valuations. The top performers in terms of valuation accuracy were EBIT, EBT and E. Schreiner and Spremann came to the conclusion that forward multiples performed more accurate valuations than trailing multiples. They discovered that the superiority of forward multiples depended largely on the choice of value driver. The latter was confirmed by Kim and Ritter (1999), who concluded that two-year EPS

forecasts outperformed one-year forecasts, while one-year EPS forecasts again dominated current EPS.

However, the only comprehensive study in this regard is offered by Schreiner (2007), who conducted an intra-category comparison of earnings-, assets-, cash flow-, knowledge- and forward-related multiples. His study included 17 trailing multiples and 10 forward multiples over the period 1996 to 2005. Categorically, Schreiner's results confirmed earlier findings in the literature regarding the superior performance of earnings-based multiples, the moderate performance of asset- and cash flow-based multiples, and the inferior performance of revenue-based multiples.[34] In particular, Schreiner found that the top performing individual value drivers in each of the five value driver categories tested were EBT, IC, CgbO, earnings before amortisation of intangibles and two-year earnings forecasts.

In one of the few documented studies conducted on the efficacy of multiples in emerging markets, Sehgal and Pandey (2010) tested the valuation performance of three value drivers, namely EPS, BVE and R. The study was conducted over the period 1993-2007 for Brazil, India, China, South Korea and South Africa. The results suggested that, while BVE was the most accurate value driver in India, China and South Korea, EPS was the most accurate value driver in Brazil and South Africa.

Unfortunately, the scope of the study by Sehgal and Pandey was limited. They selected only one value driver out of each of three value driver categories, namely earnings (EPS), assets (BVE) and revenue (R), which may have biased their design (Nel, Bruwer & Le Roux, 2014b). Sehgal and Pandey also excluded the entire cash flow- and dividend-based value driver categories, seemingly as a result of data limitations, which may have obscured their results. In addition, Sehgal and Pandey included R as a value driver in an equity-based valuation analysis, which is conceptually flawed. The matching principle is often neglected by investment

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[34] Schreiner found that adjusting earnings-based multiples for knowledge-related expenditure offered a marginal increase in the valuation performance of multiples. However, knowledge-related multiples are not elaborated on here, since accounting differences between South African and American GAAP render them nonsensical in the South African context.

practitioners and academic researchers alike, i.e. they fail to distinguish between equity- and entity-based valuations (Nel *et al.*, 2013b).

Two studies conducted in South Africa offer an emerging market perspective on the valuation performance of four value driver categories, namely earnings, assets, cash flow and revenue (Nel *et al.*, 2013d; Nel, 2010). The results compare fairly well with those of the developed markets, i.e. earnings offer superior explanatory power compared to other value driver categories, while revenue offers inferior explanatory power. In terms of valuation accuracy, asset-based multiples produce average valuations, while cash flow-based multiples produce poor valuations. However, a detailed study of the valuation performance of a multitude of individual value drivers in emerging markets, over an extended period of time, has not yet been conducted.

Consequently, the purpose of Chapter 7 is to conduct a comprehensive analysis of the valuation performance of all 16 individual value drivers over the period 2001 to 2010. The aim is to offer an emerging market perspective, detailing the valuation performance of a multitude of individual value drivers over a reasonably extended time period. In Chapter 7 a new approach is introduced for the analysis of multi-dimensional value driver research data in the form of PCA-based biplots, which are constructed to approximate graphical displays of the data.

7.3   DATA SELECTION

The number of observations differed for each value driver, depending on how well the multiples satisfied the criteria stipulated in Section 3.2. 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 to 2010. From these observations, 16 multiples were constructed, i.e. multiples where P was scaled by the 16 value drivers.

7.4 RESEARCH METHODOLOGY

The research methodology applied is similar to that explained in Section 3.4.1. The ability of equity-based multiples, based on Equation (3.1), to approximate actual share values is tested with the aim of validating H4. The valuation errors (ε_{it}) are expressed proportionally to V_{it}^e in Equation (3.4):

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

Absolute valuation errors are calculated for each entity year and subsequently aggregated. The most accurate value driver is the one with the lowest median valuation error. Consequently, the median valuation errors of the 16 value drivers are compared to establish which value drivers offer the greatest degree of valuation accuracy.[35]

The *R function CalcVEVds* was used to implement Equation (3.4). The output of *CalcVEVds,* which contained 16 pools of valuation errors (ε_{it}), was analysed with the use of the *R functions AnalyseVE* and *AnalyseVESigns*.

The initial analysis is conducted on a value driver category basis. The valuation performance of the five value driver categories is analysed by utilising singular value decomposition, together with PCA-based biplots. Thereafter, the analysis is refined to focus on individual value drivers contained in each of the five value driver categories. Firstly, boxplots are employed to conduct an intra-category comparison among value drivers, i.e. the valuation performance of the individual value drivers within each of the five value driver categories is compared to establish a performance ranking in each category. The opportunity cost associated with each sub-optimal value driver is subsequently calculated, indicating the degree of

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[35] As mentioned in Section 2.5.2.1, when employing equity-based multiples, the MPV and value drivers should match, i.e. they should both be equity-based. However, to accommodate a complete analysis, the matching requirement is relaxed and the valuation performance of all 16 value drivers is assessed.

valuation accuracy foregone as a result of a sub-optimal choice of value driver within each value driver category. Secondly, the valuation performance of the value drivers that produced the most accurate equity valuations within each of these value driver categories is compared. Thirdly, the valuation performance of all 16 value drivers is compared to ascertain whether there are incidences where individual value drivers outperform their respective categories. Fourthly, the consistency of the valuation performance of the 16 value drivers is tested over time. 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 to 2010. From the PCA biplot, an optimal one-dimensional scaling map, i.e. a one-dimensional biplot, is constructed, offering a linear display of the optimal ranking of the 16 value drivers over this period. Lastly, the tendency of multiples models based on the 16 value drivers to under- or overvalue the market is investigated.

7.5   EMPIRICAL RESULTS

The initial analysis focuses on the pooled valuation errors and does not consider the consistency of the valuation performance over time. This is followed by an analysis of the results for the years 2001 to 2010 in order to test the consistency of the results during this period. The final analysis investigates whether the 16 multiples exhibit any bias tendencies, i.e. whether they are prone to under- or overvalue the market.

7.5.1   Inter-value driver category precision based on the pooled and annual valuation errors

In this section, the valuation performance of the five categories of value drivers, namely earnings, assets, revenue, dividends and cash flow are pitted against each other. First, the modelled valuations of each of the five value driver categories are compared to the market in order to establish each category's valuation performance. Secondly, the relative valuation performance of all five value driver categories is compared and quantified. Thirdly, biplots, based on PCA, are employed to investigate the consistency of these rankings over time.

Inter-value driver category improvements were subsequently calculated, indicating the extent to which the valuation accuracy of the multiples improved by switching between value driver categories. First, the five value driver categories were ranked according to their median valuation errors in order to determine the optimal value driver category. Second, the IMP in valuation accuracy was calculated, based on substituting each of the four sub-optimal value driver categories with the optimal one. Third, the incremental IMP in valuation accuracy was calculated by adopting a step-wise substitution approach, i.e. by starting with the least accurate value driver category and continuously substituting it with the next most accurate value driver category.

The initial analysis was based on pooled valuation errors that covered the entire period between 2001 and 2010. It is equally important to consider whether the valuation performance of the value driver categories holds over time. However, the multi-dimensional nature of the data obscured a comprehensive grasp of the relative valuation performance of the five value driver categories for each observation year. Consequently, two-dimensional biplots, which are based on PCA, were constructed from the data in order to assess the behaviour of the observations over the period 2001 to 2010. A one-dimensional biplot was also constructed, offering a linear display of the optimal ranking between the value driver categories over this period.

7.5.1.1 Pooled valuation errors

In Figure 7.1, the median valuation errors are grouped per value driver category and then averaged. As is evident in Figure 7.1, the earnings-based value driver category performed the most accurate valuations, followed by the dividend-, asset-, revenue- and cash flow-based value driver categories. In terms of valuation accuracy, earnings offers good results, dividends and assets offer average results and revenue and cash flow offer poor results.

The superiority of the earnings-based value driver category becomes even more apparent when one considers the magnitude of the performance gap between the earnings-based value driver category and the other four value driver categories. The
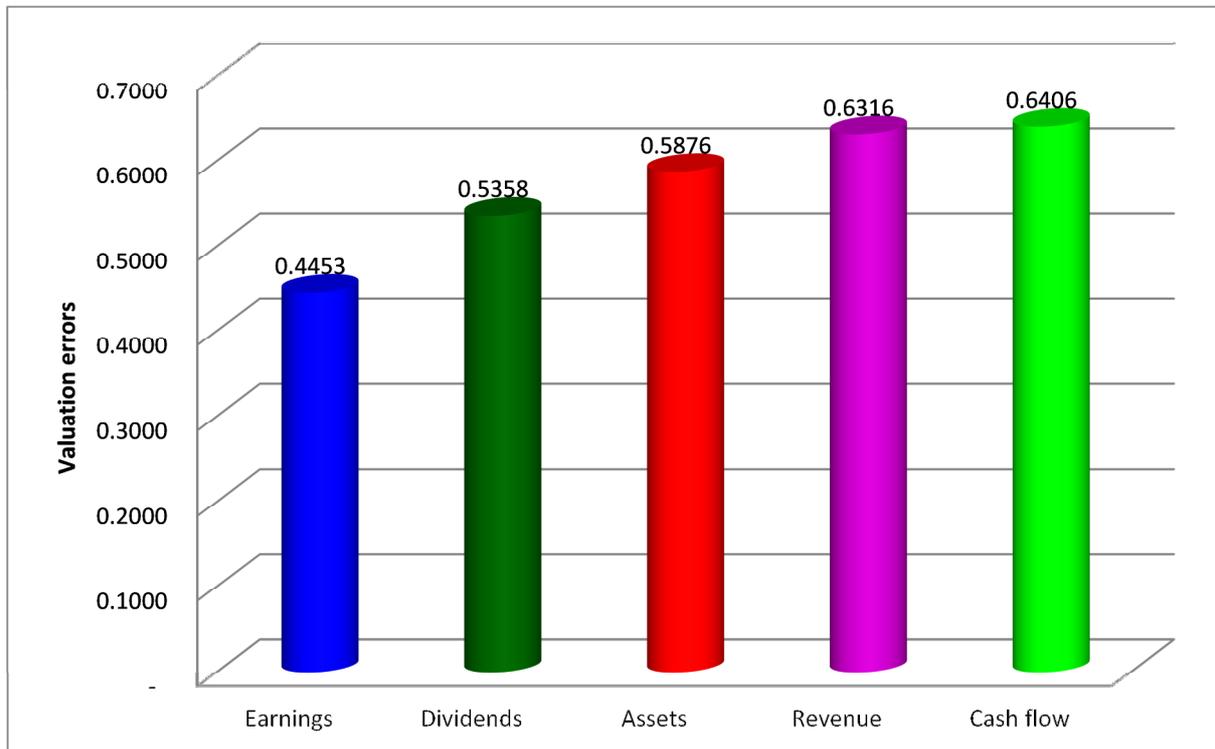
Figure 7.1: The valuation accuracy of the five value driver categories
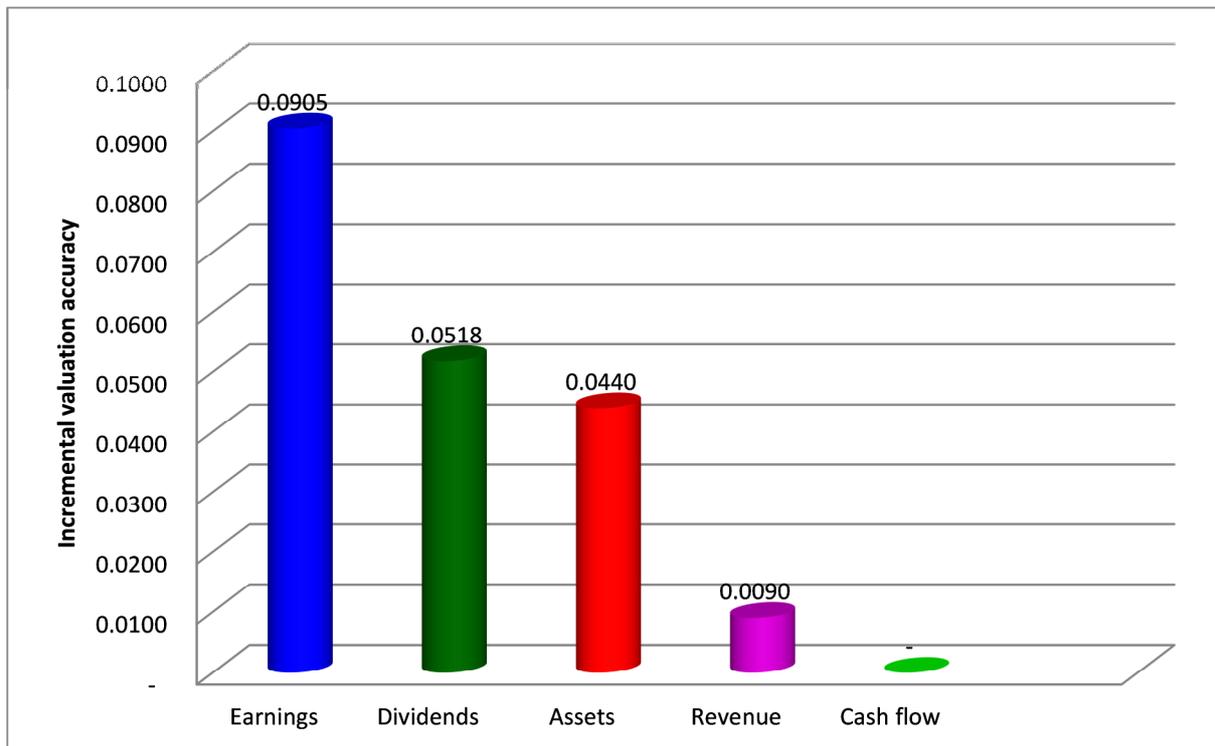
Figure 7.2: Incremental inter-value driver category improvements in valuation accuracy

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IMP in terms of valuation accuracy, when switching from the second most accurate value driver category, namely dividends, to the earnings-based value driver category, is 16.88%. The corresponding IMPs for the other three value driver categories, relative to earnings, are 24.21% (assets-to-earnings), 29.49% (revenue-to-earnings) and 30.48% (cash flow-to-earnings). A step-wise analysis of the incremental performance improvement in valuation accuracy, when moving from the worst to the best performing value driver category, is illustrated in Figure 7.2.

The results indicate that a switch from cash flow, the least accurate value driver category, to any other value driver category will improve the valuation accuracy of multiples. The most substantial improvement in valuation accuracy occurs when the switch is made to earnings.

The incremental improvements illustrated in Figure 7.2, expressed in percentage terms, are 1.41% (cash flow-to-revenue), 6.97% (revenue-to-assets), 8.82% (assets-to-dividends) and 16.88% (dividends-to-earnings). These results both concur with, and contradict, empirical evidence from developed markets. The superior performance of earnings and the inferior performance of revenue are well documented in the developed market literature (Herrmann & Richter, 2003; Liu *et al.,* 2002a; 2002b; Abukari *et al.,* 2000; Cheng & McNamara, 2000). However, evidence from the developed market literature also suggests that assets and cash flow produce average results in terms of valuation accuracy (Herrmann & Richter, 2003; Liu *et al.,* 2002a; 2002b; Abukari *et al.,* 2000; Cheng & McNamara, 2000). As is evident from Figure 7.2, cash flow produced the least accurate valuations, even inferior to that of revenue, which contradicts the evidence from the developed market literature which indicates that revenue performs the least accurate equity valuations.

The poor performance rendered by cash flow is an important discrepancy, since there is a common misconception among investment practitioners that cash flow-based multiples offer a good, if not greater, degree of valuation accuracy compared to earnings-based multiples (Liu, Nissim & Thomas, 2007). The perception regarding the credibility of cash flow as a value driver also surfaced from surveyed findings by Nel (2010), where the evidence suggested that cash flow offers superior explanatory power compared to assets and revenue. However, the evidence from the South

African market clearly contradicts evidence from the developed market literature and the common belief regarding the explanatory power of cash flow-based multiples *vis-á-vis* the other value drivers, particularly earnings-based multiples.

7.5.1.2 The multi-dimensional nature of the data and the reduction in dimensionality

The observations discussed thus far were based on pooled valuation errors for the entire period 2001 to 2010. However, these observations do not reflect the consistency of the results over this period. Table 7.1 contains an analysis of the pooled valuation errors and the annual valuation performance of the five value driver categories over time, which affords one the opportunity to assess the consistency of the results.

Table 7.1: Pooled and annual median valuation errors

		Value driver categories				
		Earnings	**Dividends**	**Assets**	**Revenue**	**Cash flow**
Pooled		0.4453	0.5358	0.5876	0.6316	0.6406
Annual	**2010**	0.4635	0.5672	0.5807	0.5751	0.6211
	2009	0.4522	0.4982	0.5308	0.6412	0.6780
	2008	0.4026	0.5462	0.5516	0.6388	0.5865
	2007	0.4226	0.5872	0.5704	0.6013	0.6517
	2006	0.4397	0.5032	0.6116	0.6762	0.6312
	2005	0.4167	0.5399	0.6083	0.6192	0.6461
	2004	0.4581	0.5389	0.5993	0.6103	0.6402
	2003	0.5100	0.4724	0.6388	0.6690	0.6267
	2002	0.4750	0.5774	0.5994	0.6278	0.6402
	2001	0.4655	0.5815	0.6497	0.7074	0.7272

However, the multi-dimensional nature of the data contained in Table 7.1 complicates a careful analysis of the general trend of the data and obscures the visibility of the consistency of the data over time. As mentioned in Section 5.5.4.1, the use of biplots accommodates the analysis of higher-dimensional data by

approximating it in lower, usually two-, dimensional space, thereby enabling the visualisation of multi-dimensional data. To this end, the valuation accuracy of the five value driver categories for the period 2001 to 2010, as measured annually by the median absolute valuation errors, is illustrated as a PCA biplot in Figure 7.3.

Years in which the earnings–based value driver category produced the most accurate valuations
Years in which the dividends–based value driver category produced the most accurate valuations
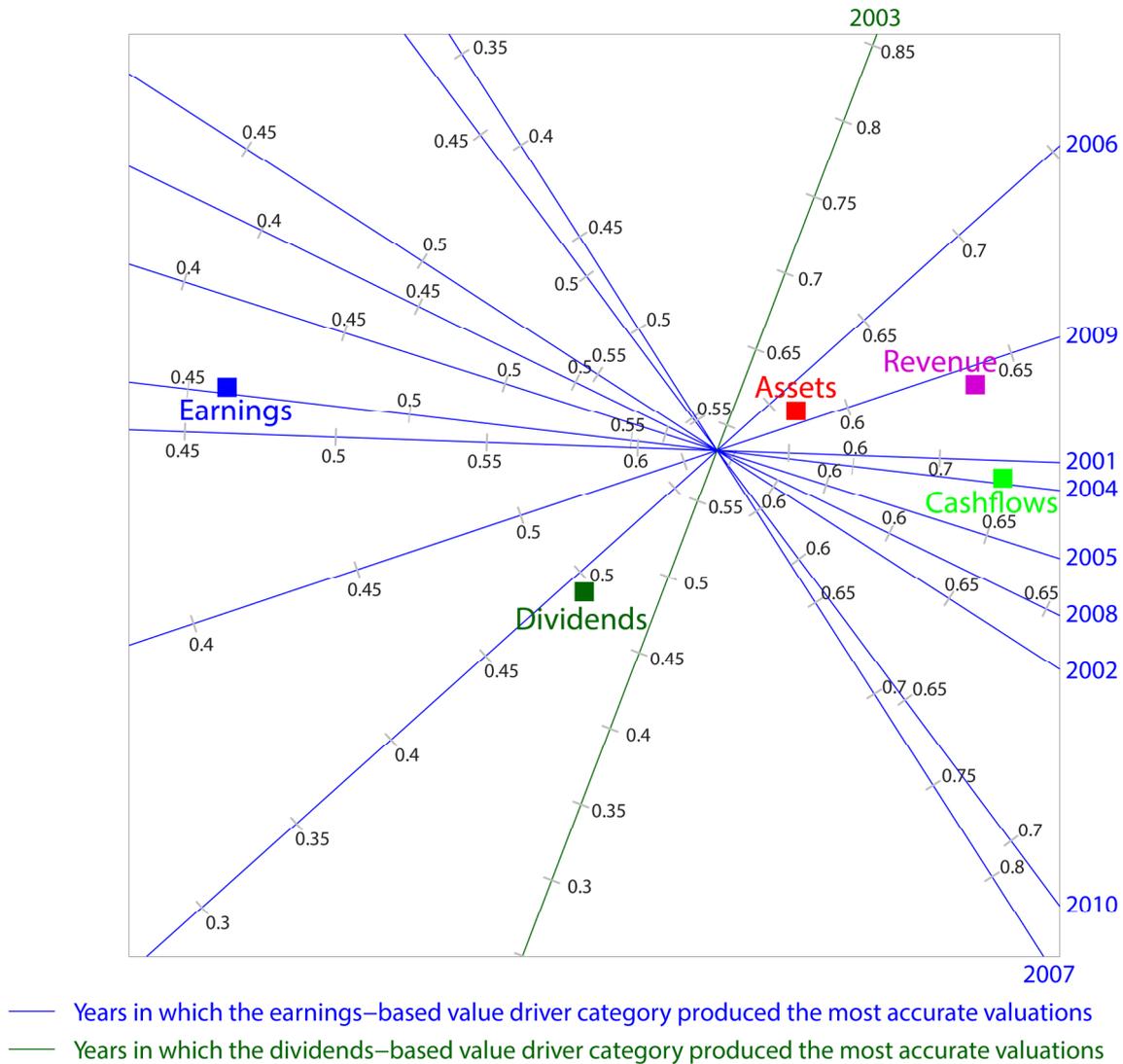
Figure 7.3: PCA biplot reflecting the consistency of the relative valuation performance of the five value driver categories over the period 2001 to 2010

Both the approximations and the actual data points of the PCA-based biplot in Figure 7.3 are contained in Table 7.2. The comparison between the actual and predicted data points over all five value driver categories in Table 7.2 indicates that the loss in data accuracy is negligible. In this analysis, the two-dimensional approximation was achieved with a PCA quality reading of 96.26% and annual predictivity readings as

Table 7.2: Value driver categories: Actual and Predicted valuation errors over the period 2001 to 2010

Year	Value driver categories									
	Earnings		**Dividends**		**Assets**		**Revenue**		**Cash flow**	
	Act	**Pre**	**Act**	**Pre**	**Act**	**Pre**	**Act**	**Pre**	**Act**	**Pre**
2010	0.4635	0.4683	0.5672	0.5715	0.5807	0.5608	0.5751	0.5913	0.6211	0.6159
2009	0.4522	0.4432	0.4982	0.5104	0.5308	0.5684	0.6412	0.6101	0.6780	0.6361
2008	0.4026	0.3979	0.5462	0.5288	0.5516	0.5712	0.6388	0.6228	0.5865	0.6222
2007	0.4226	0.4245	0.5872	0.5890	0.5704	0.5623	0.6013	0.6079	0.6517	0.6476
2006	0.4397	0.4381	0.5032	0.4959	0.6116	0.6183	0.6762	0.6707	0.6312	0.6488
2005	0.4167	0.4220	0.5399	0.5414	0.6083	0.5862	0.6192	0.6372	0.6461	0.6493
2004	0.4581	0.4617	0.5389	0.5435	0.5993	0.5841	0.6103	0.6226	0.6402	0.6337
2003	0.5100	0.5106	0.4724	0.4730	0.6388	0.6364	0.6690	0.6710	0.6267	0.6295
2002	0.4750	0.4762	0.5774	0.5758	0.5994	0.5946	0.6278	0.6317	0.6402	0.6450
2001	0.4655	0.4655	0.5815	0.5840	0.6497	0.6497	0.7074	0.7074	0.7272	0.7211

Table 7.3: Predictivity readings of the five value driver categories over the period 2001 to 2010

Years	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Predictivity	0.964	0.855	0.903	0.999	0.986	0.977	0.978	0.989	0.997	0.999

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contained in Table 7.3, confirming a negligible loss of data accuracy. The greatest loss in accuracy occurs in 2009, but, at 85.50%, it remains a very accurate approximation.

7.5.1.3 Consistency of the results

The use of biplots proved particularly useful in this study as it afforded one the opportunity to visualise the consistency of the relative valuation performances of the five value driver categories over time. In the biplot in Figure 7.3, each of the 10 years over the period 2001 to 2010 is represented by a separate calibrated axis. Note that the axes are colour-coded, i.e. each axis reflects the colour of the value driver category that performed the most accurate valuations in that particular year. As is evident from Figure 7.3, the superiority of earnings (blue axes) holds for all 10 years, except for 2003, where dividends (green axis) performed more accurate valuations.

Although, at first glance, the order in valuation performance confirms the observation in Figure 7.1, a closer examination reveals that the relative valuation performance of the value driver categories did not remain constant on an annual basis over the period 2001 to 2010. As is evident from Figure 7.3, earnings is the most consistent value driver category, since it delivers the most accurate equity valuations *vis-á-vis* the other four value driver categories for nine of the 10 years observed. Earnings is also the only value driver category that consistently delivered below average valuation errors, as is evident from its location to the left of the origin for each of the 10 years observed. Figure 7.3 also illustrates the magnitude of the superior explanatory power of earnings, which is depicted by the distance of the earnings value driver category's location from the origin and the other four value driver categories.

Figure 7.4 depicts the correlation monoplot of the median annual valuation errors, as contained in Table 7.2. Since the degrees of approximation exhibited in Figure 7.4 are all in excess of 90% it is clear that the correlation monoplot approximates the pairwise correlations among the years well. From Figure 7.4, it is further evident that

all the years are positively correlated. Therefore, all elements of the first principal component resulting from a PCA of the median annual valuation errors in Table 7.2 will have the same sign.
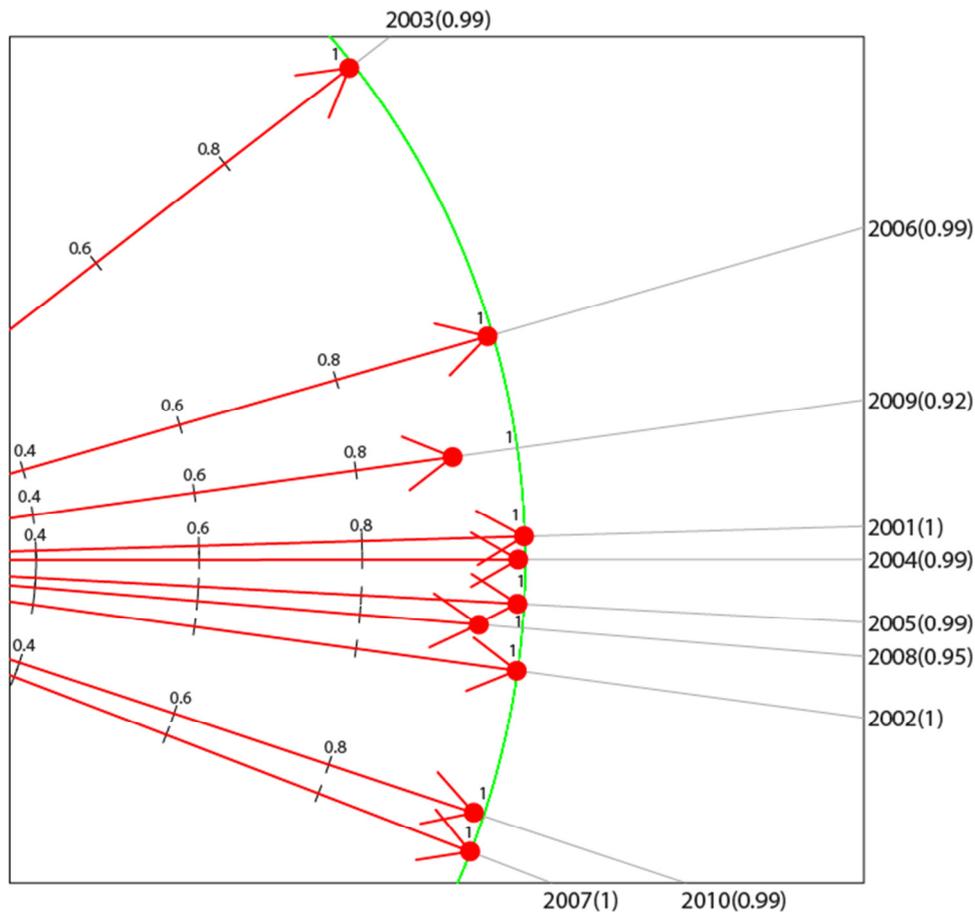
Figure 7.4: Correlation monoplot reflecting the correlations between the 10 years over the period 2001 to 2010

Consequently, the first principal component can be regarded as a size vector. From Figure 7.3, the x-coordinates of the points in the PCA biplot are used to effect a linear transformation to a convenient one-dimensional optimal performance scale for the five value driver categories. The set of optimal scores is depicted in Figure 7.5.[36]

The one-dimensional optimal scaling values, as depicted in Figure 7.5, confirm the superior valuation performance of earnings, which is located to the far left of the linear spectrum, with a scaled value of 1.4256. As with the biplot, the distance between earnings and the other four value driver categories reflects the magnitude

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[36] See Greenacre (2007) for a detailed description of optimal one-dimensional scaling.

of its superior explanatory power *vis-á-vis* the other four value driver categories over the period 2001 to 2010. The use of PCA effectively reduces the dimensionality of the data cluster, thereby affording one the opportunity to visualise the relative valuation performance of the five value driver categories with greater ease.
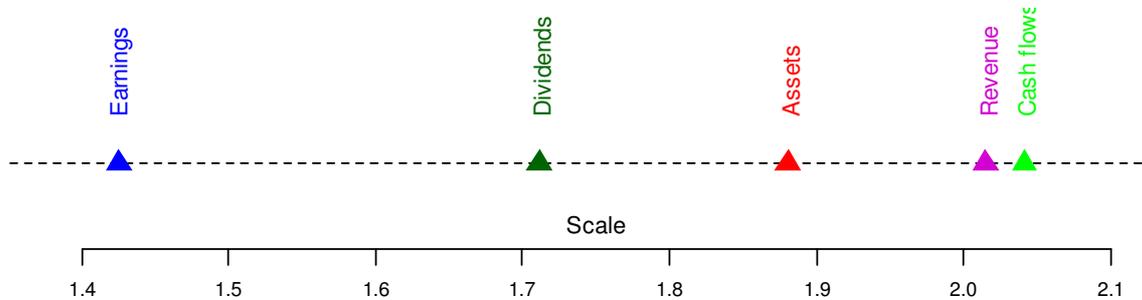
Figure 7.5: Optimal one-dimensional scaling of the relative valuation performance of the five value driver categories over the period 2001 to 2010

As is evident from Figure 7.3, dividends produced the second most accurate results over eight of the 10 years, surpassing earnings in 2003 and being surpassed by assets in 2007.[37] Dividends delivered below average valuation errors fairly consistently, as is evident from its location to the left of the origin for eight of the 10 years observed. The exceptions were 2007 and 2010. However, dividends is located a significant distance to the right of earnings in Figure 7.3 and Figure 7.5, which suggests that its valuation performance is considerably less accurate than that of earnings. The latter is reflected in its scaled value of 1.7112.

Assets produced the third most accurate results over seven of the 10 years, surpassing dividends in 2007 and being surpassed by revenue in 2010 and cash flow in 2003. Although the assets category generally tends towards the mean of the five value driver categories, it is located a significant distance to the right of earnings and dividends in Figure 7.3 and Figure 7.5, which suggests that its valuation performance is considerably less accurate than that of earnings and dividends, particularly earnings. Assets has a scaled value of 1.8805.

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[37] Note that, as was indicated in Section 5.5.4.1d, predictions can be read from Figure 7.3 by projecting orthogonal lines from any of the five value driver category points onto any of the year axes.

Surprisingly, in terms of the consistency of their valuation performance, revenue and cash flow offer similar results, with revenue offering an insubstantial increase in valuation performance over cash flow. Revenue was the second least or least accurate value driver for nine of the 10 years over the period 2001 to 2010, surpassing assets in 2010. Revenue is situated to the right of the origin in Figure 7.3, reflecting its consistent inability to produce valuation errors below the mean. Revenue produced the second least accurate valuation results over the period 2001 to 2010, with a scaled value of 2.0148.

Contrary to popular belief, cash flow produced far less accurate valuation results than earnings, which is evident from the significant distance between the locations of the two value driver categories in Figure 7.3. Cash flow was the least, or next to least, accurate value driver for nine of the years over the period 2001 to 2010, surpassing assets in 2003. Cash flow is located to the right of the origin in Figure 7.3, reflecting its poor valuation performance, i.e. it produced valuation errors higher than the mean for each of the 10 years, except for 2003. It obtained a scaled value of 2.0412, as depicted in Figure 7.5, reflecting the significance of the disparity between cash flow and earnings.

7.5.2   Intra- and inter-value driver category precision based on the pooled and annual valuation errors

In Section 7.5.1 it was established that the earnings-based value driver category performed the most accurate valuations, followed by the dividend-, asset-, revenue- and cash flow-based value driver categories. However, within each of these value driver categories there may be substantial disparities between individual value drivers in terms of their valuation performance. Although an intra-category comparison may highlight these disparities for earnings, assets and cash flow, which each contain a number of value drivers, it is nonsensical for revenue and dividends, since they contain only one value driver each.

In Figure 7.6, the valuation performance of the six earnings-based value drivers is ranked, based on their valuation accuracy. The value drivers located to the left of the boxplot produced more accurate equity valuations, i.e. they indicated lower median valuation errors than the value drivers located to the right.[38]
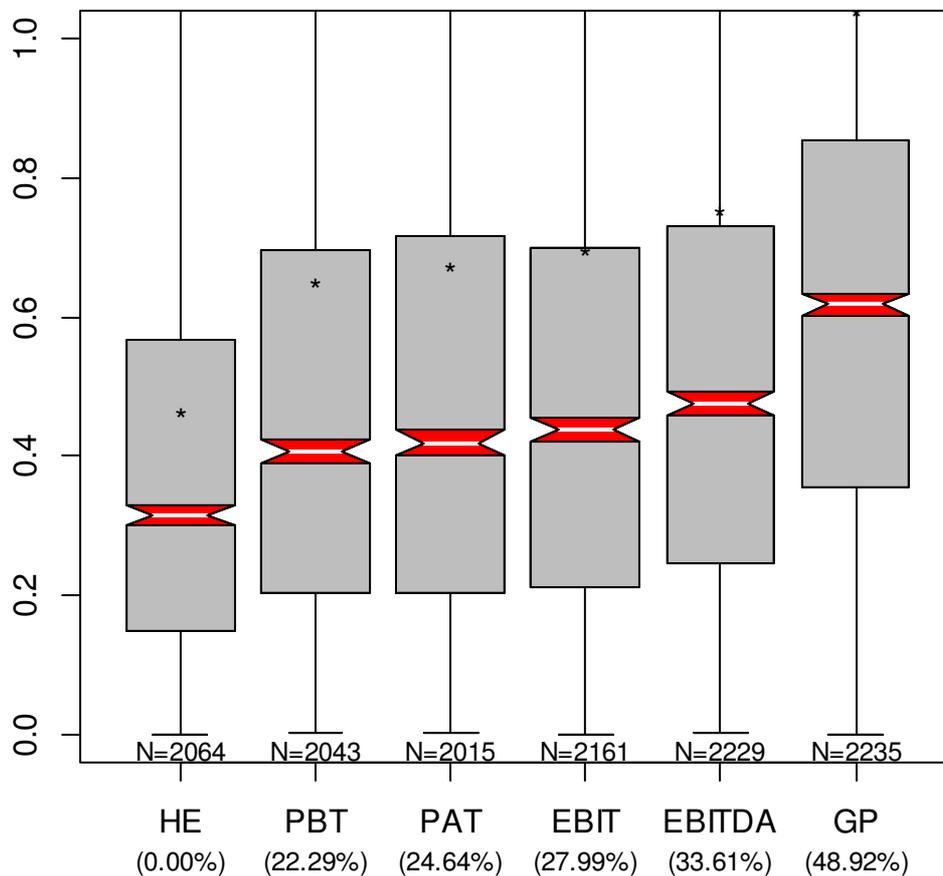
Figure 7.6: Valuation accuracy within the earnings value driver category

The optimal earnings-based value driver, i.e. the value driver that produced the most accurate valuations, is HE, which is located to the far left of the boxplot in Figure 7.6, while GP, the least accurate value driver, is located to the far right. A sub-optimal choice of value driver, i.e. the choice of any value driver other than HE, carries a potential opportunity cost (indicated as percentages in parenthesis) in terms of a foregone increase in valuation accuracy. All the opportunity cost figures are

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[38]   Note that, as is the case with most leading research, the analysis is based on the median since the mean is extremely susceptible to outliers, which were rather prevalent in the initial data analysis (Nel *et al.*, 2013a; 2013b). Since the mean valuation errors are unduly influenced (enlarged) by the outliers, the asterisks in Figures 7.6 to 7.9 are not always visible for all value drivers.

substantial, ranging from 22.29% to 48.92%, and they increase as one moves further away from the optimal value driver, i.e. HE. As is evident from Figure 7.6, GP carries the most substantial opportunity cost and is situated the furthest away from HE, reflecting an opportunity cost of 48.92%. Note from Figure 7.6 that the notches of EBITDA, EBIT and HE do not overlap with the notch of the value driver to their immediate right, indicating that EBITDA, EBIT and HE offer statistically significant improvements of the median at the 95% confidence level. The two value drivers that do not offer improvements of statistical significance are PAT and PBT.[39]
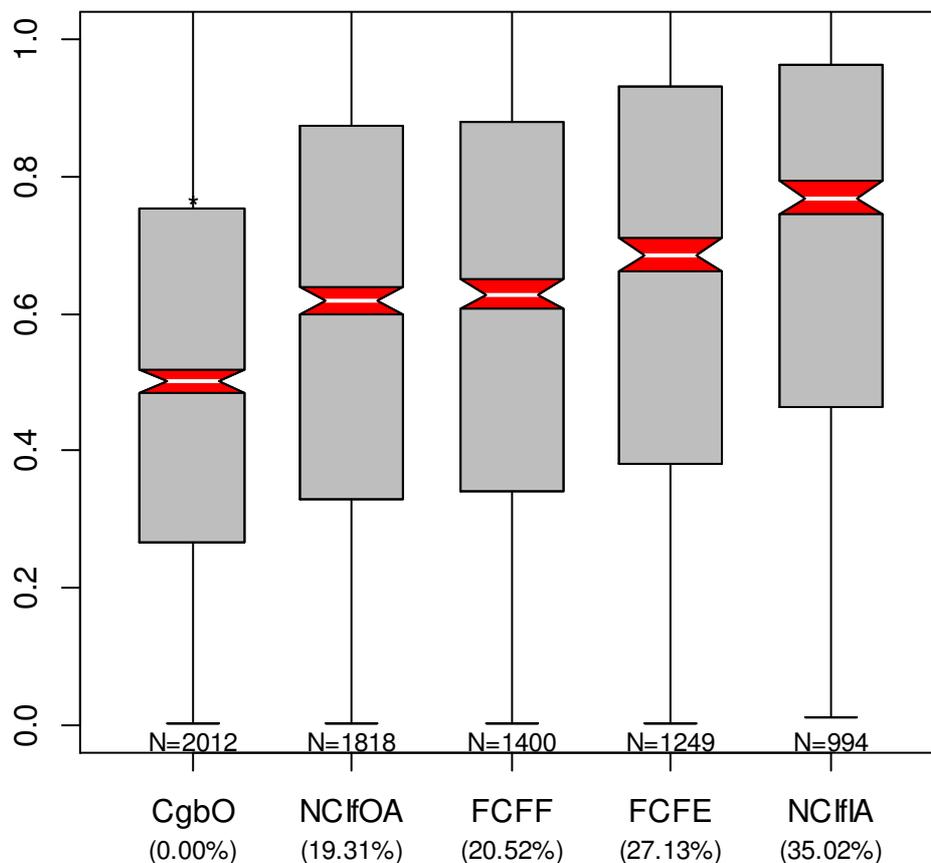
Figure 7.7: Valuation accuracy within the cash flow value driver category

From Figure 7.7, one can deduce that CgbO is the most accurate cash flow-based value driver, while NCIfIA is the least accurate. As with earnings-based value drivers,

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[39] The discussion of the statistical significance of the increase in valuation accuracy offered by each consecutive value driver in Figure 7.6 is based on their incremental explanatory power, as ranked from right to left. Evidently, when ignoring the ranking, a comparison between any of the value drivers relative to GP, for example, will reflect a statistically significant increase in valuation accuracy at the 95% confidence level.

all the opportunity cost figures are substantial, ranging from 19.31% to 35.02%. NCIfIA carries the most substantial opportunity cost and is situated the furthest away from CgbO, reflecting an opportunity cost of 35.02%. Note from Figure 7.7 that, with the exception of NCIfOA, none of the value drivers' notches overlap with the notch of the value driver to their immediate right. This indicates that all the other value drivers, namely FCFE, FCFF and CgbO, offer statistically significant improvements of the median at the 95% confidence level when they replace the value drivers situated to their immediate right.
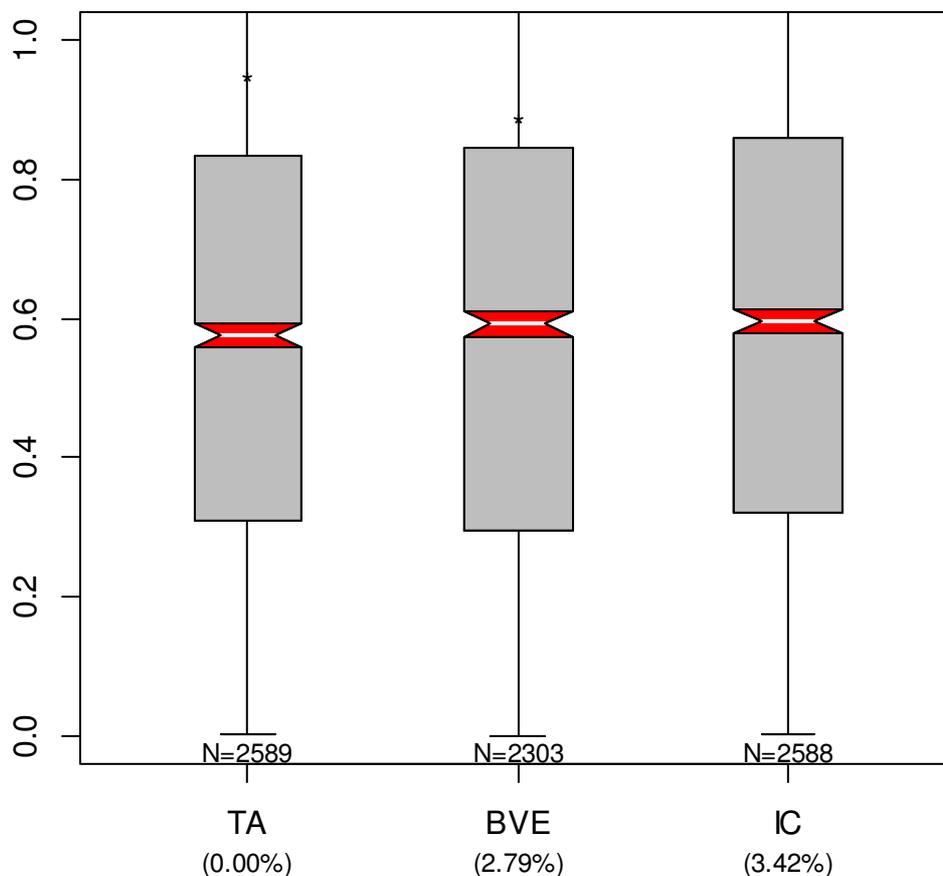
Figure 7.8: Valuation accuracy within the asset value driver category

As is evident from Figure 7.8, all three asset-based value drivers offer similar results. Although TA produced the most accurate equity valuations, the opportunity costs carried by BVE and IC of 2.79% and 3.42%, respectively, are marginal. All the notches overlap, indicating that none of the value drivers offered statistically significant improvements of the median at the 95% confidence level.

The discussion in Section 7.5.2 thus far has focused on the intra-value driver category performances of the various value drivers, highlighting the most accurate value drivers in each category. In order to determine how the most accurate value drivers in each category compare in terms of valuation performance, an inter-value driver category assessment is required. In Figure 7.9, the valuation performance of the best performing value drivers from each of the five value driver categories is compared. The optimal inter-category value driver, i.e. the value driver that produced the most accurate valuations across all five value driver categories, is HE. The least accurate inter-category value driver is R.
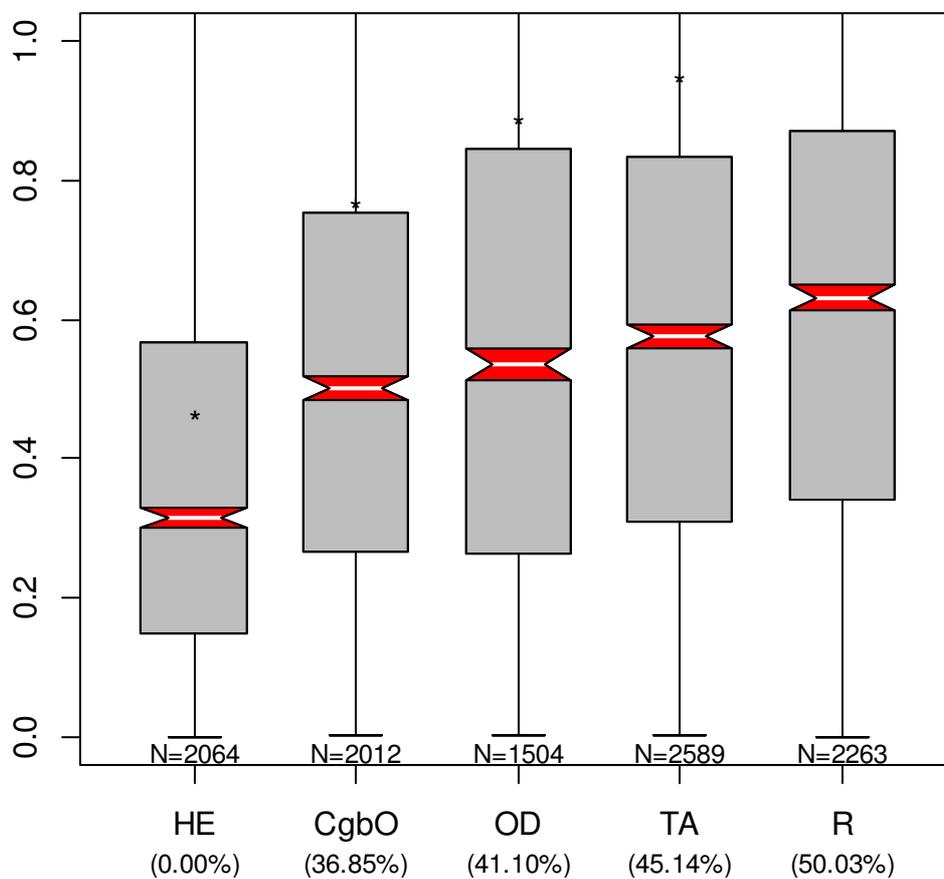
Figure 7.9: Valuation accuracy between best value drivers in each category

The inter-value driver category assessment displayed in Figure 7.9 should be viewed with the necessary amount of caution. An inter-value driver category comparison based on the selection of a single value driver from each value driver category may constitute a biased approach (Nel, Bruwer & Le Roux, 2013c). On closer examination of the observations underlying Figure 7.9, for example, one would find

that, with the exception of GP, all the individual earnings-based value drivers produce more accurate equity valuations than CgbO. The best-in-category comparison shown in Figure 7.9 merely serves to illustrate the magnitude of the superiority of HE *vis-á-vis* the other value drivers (Nel, Bruwer & Le Roux, 2014e). A more appropriate analysis would be one that compares the individual valuation performances of all 16 individual value drivers over several years.

As is evident from Figure 7.9, a sub-optimal choice of value driver, i.e. the choice of any value driver other than HE, carries a substantial potential opportunity cost, ranging from 36.85% to 50.03%. R carries the most substantial opportunity cost at 50.03%. Note that, with the exception of CgbO, which overlaps marginally with OD, none of the value drivers' notches overlap with the notch of the value driver to their immediate right, indicating that all the other value drivers offered statistically significant improvements of the median at the 95% confidence level.

7.5.3   Individual value driver precision based on pooled valuation errors

In Figure 7.10, the valuation performance of each of the 16 individual value drivers is compared. From Figure 7.10, the danger of selecting only one value driver as representative of a certain category of value drivers is evident. This approach has, however, been adopted by researchers in the past (Sehgal & Pandey, 2010; Liu *et al.,* 2002b; Cheng & McNamara, 2000). Comparing CgbO with GP, for example, may lead one to draw the wrong 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 a value driver category will bias the outcome.

An inter-value driver category comparison revealed that the earnings-based value driver category performed the most accurate valuations, followed by the assets-, cash flow- and R-based value driver categories (Nel *et al.,* 2013d).[40] However, when one considers the cross-sectional valuation performance of individual value drivers,

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[40]   Note that Nel *et al.* (2013d) 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.

there are two individual value drivers that outperform their own and/or other value driver categories. From Figure 7.10, it is evident that CgbO achieves a higher level of valuation accuracy than OD, the entire asset-based value driver category and GP. CgbO achieved a 6.72% higher valuation accuracy than OD, 13.12%, 15.55% and 16.10% higher valuation accuracies than TA, BVE and IC, respectively; and a 19.10% higher valuation accuracy than GP. Similarly, NCIfOA and FCFF outperform R by 1.93% and 0.44%, respectively. This is despite the fact that the cash flow category's inter-value driver category performance, on average, placed it last among five value driver categories. 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.
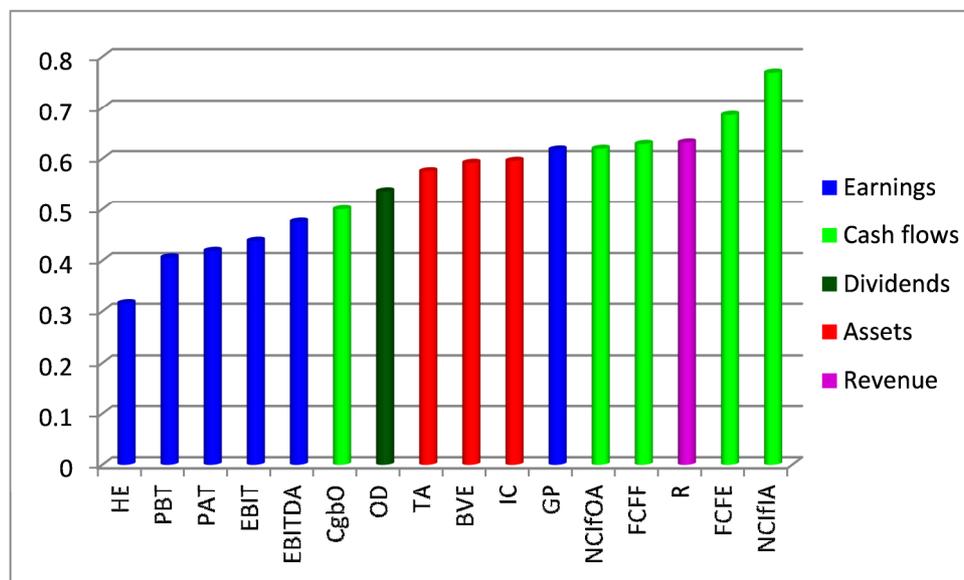
Figure 7.10: Ranking individual value drivers based on valuation accuracy

However, an analysis of the entire pool of valuation errors for the period 2001 to 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.

7.5.4 Consistency of individual value driver precision based on annual valuation errors

Table 7.4 contains a summary of the pooled and annual valuation errors of the 16 value drivers over the period 2001 to 2010. The ten-dimensional nature of the data contained in Table 7.4 complicates a careful assessment of the valuation performance of the 16 value drivers over the ten-year period. However, the PCA biplot depicted in Figure 7.11 affords one the opportunity to depict the data contained in Table 7.4 in two-dimensional space.

The PCA quality reading of the biplot in Figure 7.11 is 93.55%, suggesting that the approximations in Figure 7.11 were achieved with a negligible loss of data accuracy. This is confirmed by the annual predictivity readings, as contained in Table 7.5. The greatest loss in accuracy occurs for 2003, reflected in the predictivity reading of 82.1%, which is still very accurate.

In Figure 7.11, each of the 10 years over the period 2001 to 2010 is represented by a separate calibrated axis. The axes are colour-coded according to the value driver category that the most accurate value driver in each of the 10 years resides in. 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 below average valuation errors for each of the 10 years. Therefore, earnings-based value drivers generally produce good results in terms of valuation accuracy. Dividend- and asset-based value drivers cluster around the origin, indicating that they produce average valuation errors for each of the 10 years, i.e. they produce average results in terms of valuation accuracy. However, whereas OD produces below average valuation errors, the asset-based cluster consistently produces above average valuation errors. Revenue-based and cash flow-based value drivers, with the exception of CgbO, cluster towards the right of the origin, indicating that they produce above average valuation errors for the 10 years, i.e. they produce poor results in terms of valuation accuracy.

Table 7.4: Actual median valuation errors: Pooled and annual

	Pooled	Annual									
		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
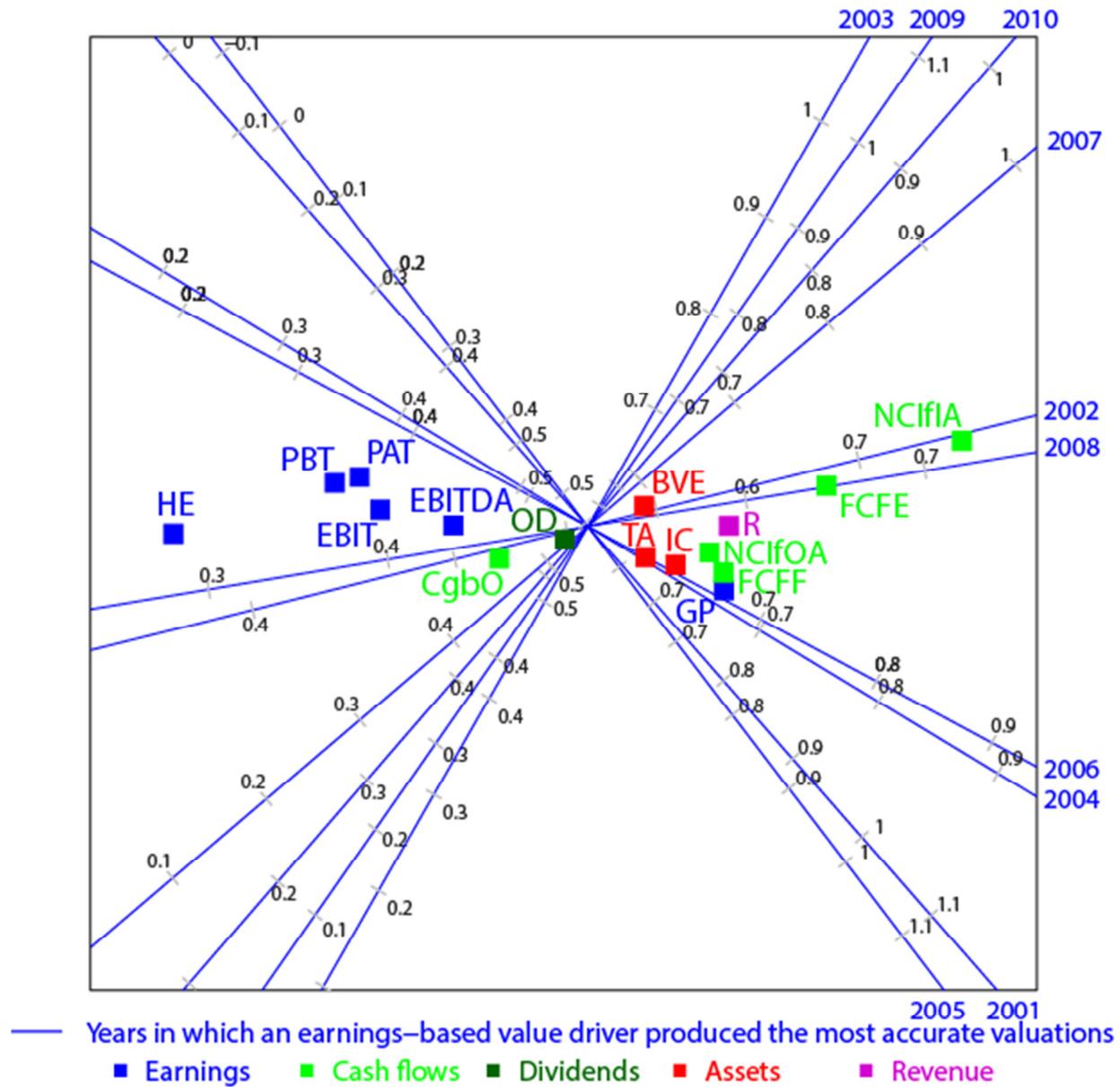
Figure 7.11: PCA biplot reflecting the consistency of the relative valuation performance of the 16 individual value drivers over the period 2001 to 2010

Table 7.5: Predictivity readings of the 16 individual value drivers over the period 2001 to 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

Table 7.6: Correlation matrix of the median annual valuation errors over the period 2001 to 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

The location of these five value driver clusters relative to each other allows one to derive their relative valuation performance in terms of valuation accuracy. Earnings-based value drivers generally perform the most accurate equity valuations. Dividend- and asset-based value drivers produce average valuation results and revenue- and cash flow-based multiples produce the least accurate valuation results. The location of the value driver clusters relative to the origin, and each other, concurs with the original findings by Nel *et al.* (2013d).

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 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 accuracy for each of the 10 years between 2001 and 2010, which is why all the axes are blue. The distance between its location in Figure 7.11 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 to 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 below average valuation errors. CgbO consistently exhibits superior explanatory power compared to the cash flow cluster in terms of valuation accuracy for each of the 10 years between 2001 and 2010. In Figure 7.11, 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 the entire group of all 16 value drivers. FCFE and NCIfIA consistently offer substantially less explanatory power compared to the other 14 value drivers. The distance between their location and that of the other 14

value drivers, and 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 performance.

Two value driver categories contained single value drivers, namely dividends and revenue. The dividend-based value driver, OD, tends towards the origin, generally producing valuation errors only marginally lower than the mean. OD consistently produces these results over the period 2001 to 2010. Revenue, on the other hand, is located to the right of the origin, reflecting its consistent sub-optimal valuation performance.

The medians of the pooled valuation errors contained in Table 7.4 (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 7.11 affords one the opportunity to assess the valuation performance of the 16 individual value drivers over the period 2001 to 2010. It offers a more comprehensive and objective view of the relative valuation performance of the 16 value drivers over time.

The correlation matrix in Table 7.6 indicates that all 10 years are highly and positively correlated, i.e. all pairwise correlations are between 0.7198 and 0.9746. Therefore, the x-coordinates of the points in the PCA biplot in Figure 7.11 can be used to effect 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 7.12. For ease of interpretation, the scores are set between a minimum of 0.3156 and a maximum of 0.7692.

Figure 7.12 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 to 2010. As with Figure 7.11, the magnitude of HE's superior valuation performance is illustrated by the distance between HE and the other 15 value drivers.

Note the dashed light blue square in the proximity of the scaling value of 0.60. The light blue square 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 light blue square are provided in the two rectangles below the original scaling in Figure 7.12.
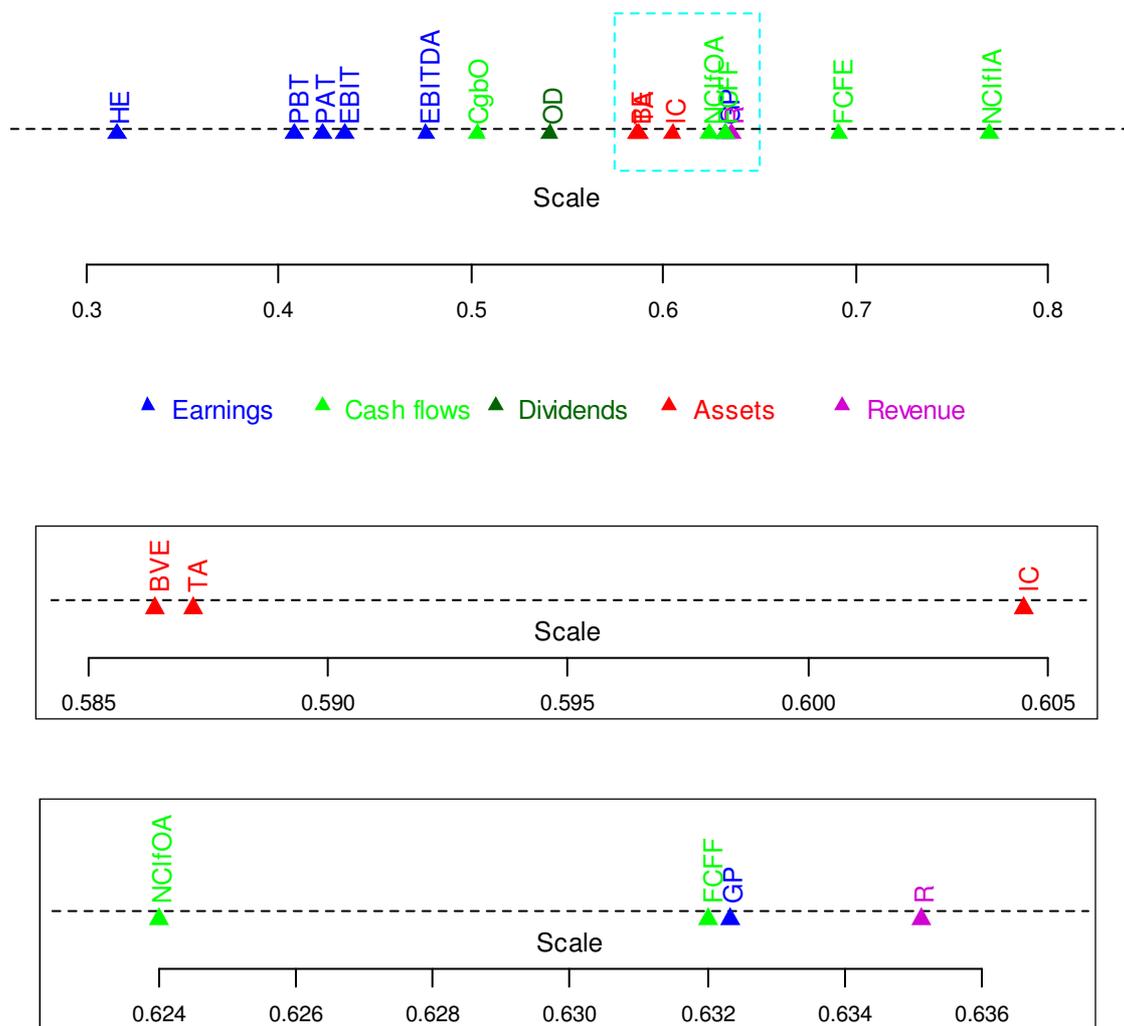
Figure 7.12: Optimal one-dimensional scaling of the relative valuation performance of all 16 value drivers over the period 2001 to 2010

The scaling values displayed in Figure 7.12 confirm the superior explanatory power offered by earnings-based value drivers and the inferior explanatory power offered by the revenue- and cash flow-based value drivers. Dividend- and asset-based value drivers offered average results in terms of valuation accuracy. Equally evident from Figure 7.12, 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.

7.5.5 Value driver bias

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 analyse the signed valuation errors. Given the design of this study, specifically the specification in (3.3), negative valuation errors (ε_{it}) will infer that multiples models tend to undervalue shares on the JSE and *vice versa*, i.e. positive ε_{it} will infer that multiples models tend to overvalue shares on the JSE.

Figure 7.13 depicts the percentiles of each of the 16 value drivers' valuation errors that exhibit negative signs. As is evident from Figure 7.13, the baseline indicates that the median signed valuation errors are predominantly negative, which suggests that all 16 value drivers tend to undervalue JSE shares.

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 is the main reason that 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).
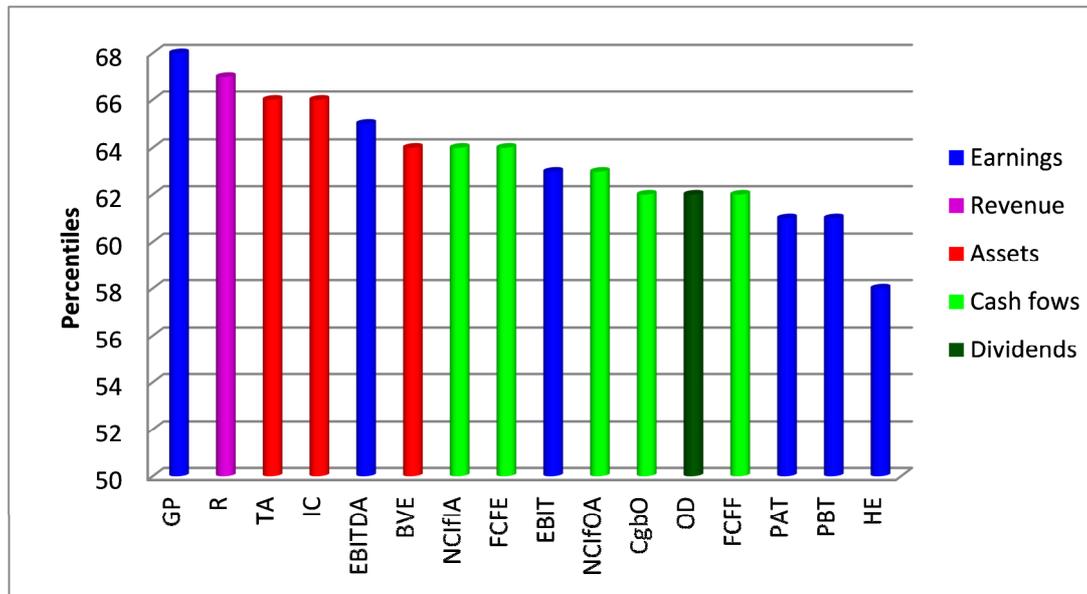
Figure 7.13: Percentiles of valuation errors exhibiting negative signs

As is evident from Figure 7.13, the magnitude of the multiples models' 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.

7.6   CONCLUSION

The main contribution of Chapter 7 is that it offers an emerging market perspective on the degree of value relevance of five value driver categories, namely earnings, dividends, assets, revenue and cash flow. Although all 16 value drivers proved to be value relevant, i.e. they all carry information content that affects the market price of shares, they exhibited various degrees of value relevancy. The empirical evidence suggests that earnings offer the greatest degree of valuation accuracy *vis-á-vis* dividends, assets, revenue and cash flow. In terms of valuation accuracy, the latter four value driver categories offer distant alternatives to earnings. Compared to earnings, dividends and assets offered moderate results, while revenue and cash flow offered poor results. With the exception of revenue and cash flow, these findings concur with empirical evidence from the developed market literature. Therefore, the

research results verified H4, in that multiples models that are constructed on earnings-based value drivers offer higher degrees of valuation accuracy *vis-á-vis* multiples models that are constructed on dividend-, asset-, revenue- or cash flow-based value drivers.

However, while the developed market literature suggests that cash flow produces average results, the findings in this study indicate that cash flow offers poor results. The evidence also suggests that, depending on the selection of value drivers included in the cash flow-based value driver category, revenue, in fact, could offer a greater degree of valuation accuracy compared to cash flow, which also contradicts evidence from the developed market literature. The latter would occur, for example, when OD is omitted from the cash flow-based value driver category and regarded as a dividend-based value driver instead.

The study employed PCA-based biplots to investigate the consistency of the relative valuation performance of the five value driver categories over time. Given the multi-dimensionality of the data contained in this study, biplots seem to be a promising tool for analysing and visualising multi-dimensional data of this nature. The consistency of the results, i.e. the ability of the respective value driver categories to maintain their valuation performance on an annual basis throughout the period 2001 to 2010, confirmed the initial findings. All five value driver categories offered fairly consistent valuation results over this period, i.e. their value relevance did not vary substantially over this period.

Consequently, the research results present strong evidence in support of the use of earnings as a superior value driver when employing multiples to perform equity valuations, which concurs with empirical evidence from developed capital markets. The evidence therefore suggests that earnings-based value drivers are highly value relevant, which, in turn, justifies investment practitioners' preference for earnings-based multiples.

However, the evidence rejects the general perception that cash flow-based multiples offer relatively accurate valuations compared to earnings-based multiples. The opportunity benefit of switching from cash flow- to earnings-based value drivers

could provide an increase in valuation accuracy of up to 30.48%, which is substantial. Consequently, cash flow-based value drivers carry a lesser degree of value relevance compared to earnings-based value drivers, which suggests that investment practitioners who rely on cash flow-based multiples should consider switching to earnings-based multiples.

The second contribution of Chapter 7 is that it quantifies the magnitude of the potential improvement in valuation accuracy when substituting a less accurate value driver category with a more accurate one. Based on the median valuation errors, the potential improvement in valuation accuracy lies between 1.41% and 16.88%. It is therefore evident that investment practitioners can, by switching value driver categories, substantially improve the valuation accuracy of their multiples models.

The analysis in Chapter 7 also focused on the valuation performance of the individual value drivers that resided in each of the five value driver categories. Firstly, an intra-value driver category comparison within each of the value driver categories revealed that HE was, by far, the most accurate value driver in the earnings-based value driver category. The loss of accuracy associated with each sub-optimal choice of value driver within the earnings-based value driver category indicated a substantial opportunity cost, ranging from 22.29% to 48.92%. CgbO surfaced as the most accurate value driver in the cash flow-based value driver category, with a sub-optimal opportunity cost range of 19.31% to 35.02%. No superior value driver emerged from the asset-based value driver category, as all three value drivers in this category yielded similar results.

Secondly, the valuation performance of the five best performing value drivers from each of the value driver categories was compared. HE was the value driver that produced the most accurate valuations across all five value driver categories, while R produced the least accurate valuation results. The results revealed that a sub-optimal choice of value driver carried a substantial potential opportunity cost, ranging from 36.85% to 50.03%. However, these results highlighted the danger of selecting single value drivers as representatives of entire value driver categories. This tendency, which may constitute a biased approach, seemed to have crept up in

previous research. Therefore, a more appropriate comparison was performed, where the valuation performance of all 16 individual value drivers was considered. Thirdly, therefore, the evidence suggests that certain individual value drivers 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 accuracy ranging between 6.72% and 19.10%. Similarly, NCIfOA and FCFF outperformed R by 1.93% and 0.44%, respectively, while the entire asset-based value driver category outperformed GP by an increased level of accuracy, ranging from 3.58% to 6.88%.

Fourthly, the consistency of the valuation performance of the 16 value drivers was tested over the period 2001 to 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 a superior degree of valuation accuracy for each of the 10 years between 2001 and 2010. All three asset-based value drivers were fairly closely located, indicating that they all offer similar results in terms of valuation performance. OD tended towards the origin, generally producing valuation errors only marginally lower than the mean over the period 2001 to 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 10 years between 2001 and 2010. The worst valuation performances were undoubtedly produced by FCFE and NCIfIA,

which consistently reflected substantially less value relevance compared to the other 14 value drivers.

Lastly, the evidence also suggests that multiples-based modelling 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, as many as two thirds of the observations exhibited a predominant tendency to undervalue share prices on the JSE.

This research evidence from Chapter 7 has shown that, with the exception of GP, investment practitioners should scale market prices with earnings-based value drivers, specifically HE, when constructing multiples. South African investment practitioners, particularly proponents of EBITDA and EBIT, should take cognisance of the fact that EBITDA and EBIT are fourth and fifth best earnings-based alternatives, which largely contradicts evidence from the developed markets. Equally evident from the results is that, with the exception of CgbO, cash flow-based multiples offer a dismal valuation performance, i.e. they are less value relevant compared to earnings-based multiples. Therefore, cash flow-based multiples should preferably be replaced with more accurate earnings-based multiples. Revenue also offers a poor valuation performance and should preferably be avoided, if possible.

The academic contribution of Chapter 7 relates to the choice of value drivers for inclusion in a study of this kind. The evidence suggests that the selection of a single value driver as representative of a specific value driver category constitutes a biased design and may produce misleading results.

The findings also offer a practical perspective, in that multiples-based modelling seems to be biased to the downside. This is an important consideration for investment practitioners who choose to adjust their valuations outside of these models, which is a common phenomenon in practice.

Based on the cross-sectional results obtained from Chapters 4 to 7, one is able to construct optimal single factor multiples models, as demonstrated in Chapter 7.

However, these optimal single factor multiples models are based on the market as a whole, i.e. they are not industry-specific. As such, these market-based single factor multiples models cannot be compared with optimal composite models, whose construction is industry-specific. Therefore, in order to compare the relative valuation performance of optimal single factor multiples models with that of the composite models, one needs to ascertain whether the market-based single factor multiples models perform equally well when subjected to an industry analysis. This is explored in further detail in Chapter 8.

CHAPTER 8

INDUSTRY-SPECIFIC MULTIPLES

8.1   INTRODUCTION

The investigation in Chapter 8 aims to establish whether the optimal single factor multiples, based on the market as a whole, i.e. based on the results from Chapters 4 to 7, hold equally well on an industry basis. If the optimal, market-based, single factor multiples do not hold when subjected to an industry analysis, they will be substituted with industry-specific optimal single factor multiples.

Consequently, the main objective of Chapter 8 is to answer research question five by investigating whether empirical evidence exists to support the common practice of using industry-preferred multiples and, in so doing, to verify H5, which postulates:

H5:   The valuation accuracy of multiples is industry-specific, i.e. the optimal choice of value driver depends on the industry in which the target entity resides.

Apart from establishing whether such preferences are warranted, it is also envisaged that these preferences may not be based on optimal PGVs. The second aim, therefore, is to revisit the peer group selection methods discussed in Chapters 4 and 5, on a per-sector basis, in order to ascertain which PGVs are best suited to which sectors.

Thirdly, a Sector Value Chain (SVC) is created, offering a guide to investment practitioners in terms of the optimal choice of multiples for entities residing in each of the 28 sectors that are analysed. To this end, 448 multiples are constructed, 16 multiples for each of the 28 sectors demarcated on the McGregor BFA database.

An industry-specific approach to multiples seems intuitively logical. For example, one might anticipate that asset-based multiples may be more appropriate in capital intensive industries compared to consultancy-based industries. However, a number of underlying questions lie embedded in an industry-specific approach: Firstly, which specific multiples produce the most accurate valuations in which industries? Secondly, do these industry-specific superior multiples perform the most accurate valuations in the respective industries consistently over time? Thirdly, what is the magnitude of the opportunity cost involved when employing suboptimal multiples, i.e. does an industry-specific approach to multiples-based valuations matter? The emerging market literature offers little insight in to these issues. It is envisaged that Chapter 8 will offer a South African perspective, which could act as an empirical guide to investment practitioners in this respect.

8.2   LITERATURE REVIEW

Popular belief suggests that different industries have different "best" multiples (Liu *et al.,* 2002a). In a study conducted on UK and European industries, Fernández (2001) found that investment practitioners have a preference for certain multiples in certain industries, which supports the notion that different multiples are best suited to different industries. A similar conclusion was drawn by Abukari *et al.* (2000) in a study of equity valuation techniques based on entities listed on the Toronto Stock Exchange.

Although, in practice, different multiples are regarded as best suited to different industries (Schreiner, 2007), the literature offers surprisingly little evidence in support of this phenomenon. Research on specific multiples has largely focused on price multiples, typically including a discussion of the P/EPS ratio. In all likelihood, this stems from the general perception that the P/EPS ratio is the preferred multiple in equity valuations. Despite evidence presented by Nel (2009a) to the contrary, executives may nevertheless be tempted to orchestrate a high P/EPS ratio (Chadda *et al.,* 2004). It is possible that the fascination with the P/EPS ratio, at least in part, stems from the attention that is bestowed upon it by the media. However, as alluded to in Chapter 2, one needs to remain cognisant of two key factors in this respect,

namely the quality of the earnings contained in the earnings-based value driver and its susceptibility to earnings manipulation.

Barker (1999) found similar results in the UK market. He conducted survey- and market-based research among 64 UK investment practitioners in 1995 and found evidence in support of the notion that investment practitioners have different preferences for different industries. The results indicated that, although the P/EPS ratio is the primary multiple used by investment practitioners, this is not the case across all industries. The survey results indicated that the dividend yield surpassed the P/EPS ratio in the utilities and financial industries, for example (Barker, 1999).

In the only documented study conducted on the South African market in this regard, Nel (2009a) compared the valuation performance of the five most popular multiples that are used in practice by South African investment practitioners, three equity-based multiples and two entity-based multiples, over the period 1988-2007. The research results indicated that both South African investment practitioners and academics have a preference for the use of the P/EPS ratio (Nel, 2010; PwC, 2010). However, the results indicated that the P/EPS ratio only performs the most accurate valuations in 25% to 33% of the sectors on the JSE (Nel, 2009a). The results also indicated a potential performance improvement of between 3% and 46%, in terms of valuation accuracy, among those sectors where the P/EPS ratio was not the most accurate multiple, i.e. where MVIC/EBITDA, MVIC/EBIT, P/PBT or P/BVE performed a more accurate valuation.

Apart from the study done by Nel (2009a), the literature offers little evidence on the valuation performance of multiples over various sectors in South Africa. Chapter 8 aims to address the lack of empirical evidence in this regard and to enhance the previous work done by Nel in two ways. Firstly, it extends the number of multiples from five to sixteen, with the aim of deriving a more complete reference base for industry-preferred multiples. Secondly, it covers five different value driver categories, as opposed to only focusing on earnings and BVE, as was the case previously.

8.3   DATA SELECTION

The number of observations varied for each multiple, depending on the peer group selection method and variable applied and how well the multiples satisfied the criteria stipulated in Section 3.2. Consequently, the population sizes of the multiples vary between 433 and 2 684 observations, culminating in a total population size of 260 982 observations. From these observations, 16 multiples were constructed; i.e. multiples where P was used as the MPV.

8.4   RESEARCH METHODOLOGY

While a cross-sectional analysis was conducted in Chapters 4 to 7, an industry-analysis approach is adopted in Chapter 8. The methodology applied is similar to that applied in Chapter 7, with the exception that the analysis is conducted on a sector basis, whereas previously the analysis was conducted on the market as a whole. Therefore, the out-of-sample estimates of the peer group multiple ($\hat{\lambda}_{pt}^{e}$) for each entity were based on the 10 different PGVs identified in Chapter 5, compiled for each of the 28 sectors. A sector-based analysis was conducted, since SEC was the most descriptive industry classification available, compared to IND and SUP, and also prevented a substantial loss of data, which would have occurred had the SUB industry classification been used. A target entity's $\hat{\lambda}_{pt}^{e}$ was calculated based on the harmonic mean of all the other remaining entities in the target entity's peer group.

All the functions containing the term *peergroup* were written in *R code* to accommodate the calculation of the valuation errors (ε_{it}) in Chapter 8. These ε_{it} were analysed with the use of the *R function AnalyseVE.*

The construction of multiples based on a target entity's industry classification is a common phenomenon (Nel, Bruwer & Le Roux *,* 2014c; 2013a; Nel, 2009a; 2009b; Goedhart *et al.,* 2005; Liu *et al.,* 2002a; Fernández, 2001; Barker, 1999). So, too, is a multiples-based valuation approach where peer groups are based on valuation fundamentals (Nel, Bruwer & Le Roux*,* 2014a; 2014c; Henschke & Homburg, 2009; Dittmann & Weiner, 2005; Goedhart *et al.,* 2005; Herrmann & Richter, 2003; Bhojraj & Lee, 2002).

The multiple that produces the most accurate equity valuation in each sector will typically be the one with the lowest summarised valuation error. In order to establish which multiples are best suited to which sectors, an SVC is created, ranking the multiples according to the precision of their equity valuations. The SVC indicates the IMP in valuation accuracy that may be secured by employing a more accurate multiple, i.e. by substituting a less accurate multiple with a more accurate multiple.

8.5 EMPIRICAL RESULTS

In Chapter 7, the valuation performances of 16 multiples were subjected to a cross-sectional analysis in order to establish which value drivers performed the most accurate equity valuations in the market as a whole. In Chapter 8, an industry analysis is conducted in order to ascertain which multiples are best suited to which sectors, i.e. which multiples produce the most accurate equity valuations within each sector. However, in order to do so, one must first determine which PGVs are best suited to which sectors. It is anticipated that an industry analysis of PGVs may yield different results to those obtained from Chapter 5, which, in turn, may influence the valuation accuracy of individual value drivers in each sector. In order to gain a clear perspective on the valuation performance of the 16 multiples, an SVC is created, ranking the multiples within each sector according to their valuation accuracy.

8.5.1 The impact of peer group selection on the valuation accuracy of multiples

In order to ascertain which multiples should be used in which sectors, it is imperative to first identify the most appropriate basis for peer group selection. This can be gleaned from Table 8.1, which contains the average median valuation errors for each sector, based on 10 PGVs. The most accurate valuations, on average, per sector are indicated in bold. The IMP.PGV column on the far right of Table 8.1 indicates the IMP between the least and the most accurate PGV. In the Equity Investment Instruments sector, for example, employing any of the industry classifications, other than IND, as the PGV rather than TA.Rg, could improve the valuation accuracy by 83.18%, which is a substantial gain in precision.

From Table 8.1, it is evident that 57.14% of the sectors indicated that multiples whose peer groups are based on industry classification produce more accurate valuations than those whose peer groups are based on valuation fundamentals. When one considers the individual valuation performance of the multiples whose peer groups are based on each of the 10 PGVs, it is evident that there is no consistent superior PGV across all 28 sectors. SUP, SEC and RoE.TA each produced the most accurate multiples, on average, in approximately five of the 28 sectors.[41] RoE.Rg produced the most accurate multiples, on average, in four of the sectors and IND, SUB and TA.Rg each produced the most accurate multiples in approximately three of the sectors. As was the case with the cross-sector analysis performed in Chapter 7, the single factor fundamentals consistently produced the least accurate equity valuations over all 28 sectors.

However, the range of IMP.PGV exhibited between the least and most accurate peer group selection methods over all 28 sectors is 15.30% to 83.18%, which is substantial. The results, therefore, warrant a sector-specific approach to peer group selection. For example, when multiples are constructed for entities in the Financial Services sector, peer group selection should focus on the valuation fundamental RoE.Rg. However, when multiples are constructed for entities in the Mining sector, peer group selection should focus on the SUB industry classification.

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[41] Note that the Banking, Construction and Materials and Equity Investment Instruments sectors have more than one optimal PGV. In the Banking sector, for example, the industry classifications SUP, SEC and SUB, all exhibited the same valuation error, namely 0.5100. This implies that all three these industry classifications contain the same peer groups. Consequently, in the Banking sector, for example, SUP, SEC and SUB are each allocated an optimal PGV fraction score of a third (0.33), which is why their column totals in the line "Optimal performance: Number of sectors", in Table 8.1, contain fractions. Similarly, in the Construction and Materials sector, SUP and SEC are each allocated an optimal PGV fraction score of a half (0.50).

Table 8.1: Median valuation errors per sector, based on 10 PGVs

	Industry Classification				Fundamentals						IMP.PGV
	IND	SUP	SEC	SUB	RoE	TA	Rg	RoE.Rg	RoE.TA	TA.Rg	
Banks	0.5684	**0.5100**	**0.5100**	**0.5100**	0.7976	0.7217	NA	NA	0.5910	NA	36.05%
Beverages	0.5317	**0.3894**	0.4618	NA	0.6760	0.5810	0.6419	0.5265	0.4543	0.5573	42.40%
Chemicals	0.4757	0.5042	0.5042	0.5042	0.5094	0.4971	0.5477	0.4654	**0.4639**	0.4927	15.30%
Construction & Materials	0.5299	**0.5075**	**0.5075**	0.5196	0.5899	0.6250	0.6049	0.5287	0.5657	0.6023	18.80%
Electronic & Electrical Equipment	**0.5582**	0.5684	0.6156	0.6510	0.6752	0.7191	0.8266	0.6616	0.6279	0.6152	32.48%
Equity Investment Instruments	0.6763	**0.6731**	**0.6731**	**0.6731**	0.8395	0.9368	1.2093	1.4236	0.7153	4.0008	83.18%
Financial Services	0.6109	0.6493	0.6493	0.7043	0.7628	0.8351	0.7227	**0.5226**	0.5260	0.7327	37.43%
Food & Drug Retailers	0.5900	0.6431	**0.4044**	0.4466	0.5935	0.6072	0.5749	0.4934	0.4667	0.5406	37.12%
Food Producers	0.4869	0.4406	0.4640	0.4738	0.5301	0.5362	0.5627	0.4628	**0.4403**	0.5447	21.74%
Forestry & Paper	0.9191	0.9544	0.7301	NA	0.7261	0.7947	0.7093	1.6772	**0.5275**	1.7752	70.29%
General Industrials	0.4903	0.5138	0.4187	0.4480	0.4412	0.5160	0.4759	**0.4174**	0.4380	0.5651	26.13%
General Retailers	0.6048	0.6603	0.6998	0.6985	0.6312	0.6169	0.6231	0.5223	0.5431	**0.5028**	28.15%
Industrial Engineering	0.4761	0.4861	0.5875	0.5950	0.4933	0.6173	0.6038	**0.4392**	0.5018	0.7164	38.70%
Industrial Metals & Mining	**0.5507**	0.5684	0.6176	0.6342	0.7983	0.8367	0.8029	0.8670	0.6993	1.0287	46.47%
Industrial Transportation	0.5332	0.5372	0.5285	**0.4894**	0.6248	0.6897	0.6888	0.7592	0.7721	0.9569	48.86%
Life Insurance	0.6523	0.6393	0.6540	0.6540	0.8759	0.6582	1.0969	0.7009	0.6278	**0.6080**	44.57%
Media	0.6391	0.6407	0.6407	NA	0.6511	0.7073	0.6654	0.6130	**0.5502**	0.5508	22.21%
Mining	0.6043	0.6087	0.5851	**0.5510**	0.8466	0.8969	0.8074	0.6479	0.8215	0.7445	38.57%
Mobile Telecommunications	0.4656	0.4656	0.4772	0.4772	0.5093	0.5568	0.5486	0.4398	**0.4085**	0.6718	39.18%
Non-life Insurance	0.4921	0.4891	**0.4708**	NA	0.6004	0.6907	0.6130	0.5837	0.6910	0.6914	31.91%
Personal Goods	0.8137	0.9090	0.9449	NA	0.8444	0.9141	0.9677	0.7559	0.6308	**0.5231**	45.94%
Pharmaceuticals & Biotechnology	0.4253	0.4437	**0.4173**	0.4173	0.7102	0.7286	0.7071	0.4544	0.5939	0.6416	42.73%
Real Estate Investment & Services	0.6554	**0.6179**	0.6376	0.6376	0.9813	0.9466	0.9251	0.7904	0.8090	0.8883	37.03%
Real Estate Investment Trusts	0.6558	0.5205	**0.3010**	0.3530	0.6372	0.6709	0.6968	0.6839	0.6053	0.7342	58.99%
Software & Computer Services	0.4866	**0.4866**	0.4902	0.5023	0.5632	0.6364	0.5757	0.5075	0.5887	0.6144	23.55%
Support Services	**0.4452**	0.4563	0.4953	0.5645	0.6513	0.6115	0.7542	0.7237	0.5592	0.5179	40.97%
Technology Hardware & Equipment	0.4533	**0.4533**	0.5145	0.6194	0.6282	0.6332	0.6649	0.6300	0.6204	0.7976	43.16%
Travel & Leisure	0.5805	0.4827	0.4827	0.6477	0.5825	0.6498	0.5906	**0.4708**	0.5573	0.5800	27.55%
Optimal performance: Number of sectors	3	5.17	5.17	2.67	0	0	0	4	5	3	
Percentage of sectors	10.71%	18.45%	18.45%	9.52%	0.00%	0.00%	0.00%	14.29%	17.86%	10.71%	
TOTAL	16 (57.14%)				12 (42.86%)						28 (100.00%)

Note: The NAs denote situations where there were insufficient entities to constitute a peer group.

A comparison between these results and the results obtained from the peer group analysis conducted in Chapter 5 highlights interesting similarities and disparities. The results in Chapter 5 suggested that multiples whose peer groups are based on a combination of valuation fundamentals, notably RoE.Rg, offered superior explanatory power *vis-à-vis* multiples whose peer groups are based on industry classifications.

In Chapters 4 and 5, a cross-sectional analysis was performed on the valuation accuracy of multiples whose peer groups were based on four different industry classifications and three different valuation fundamentals, or combinations thereof. The results of the industry analysis displayed in Figure 8.1 confirm the earlier findings in Chapters 4 and 5.

In Figure 8.1, 22 sectors are depicted by 22 coloured (green, blue and red) squares, indicating which PGV produced the most accurate valuation in any particular sector.[42] From the green squares depicted in Figure 8.1, it is evident that the valuation accuracy of the multiples whose peer groups were based on the four industry classifications depends on the specific sector in question. The Real Estate and Investment Trusts (REIT) sector, for example, is depicted by a green square, suggesting that peer group selection based on industry classification, SEC in particular, is the optimal choice for this sector.

Similarly, from a fundamental variable approach perspective, multiples whose peer groups are based on single valuation fundamentals produced the least accurate equity valuations over all the sectors reported on. In Figure 8.1, the three single valuation fundamentals are indicated by the red axes, labelled TA, Rg and RoE. Note that there are no red squares in Figure 8.1, indicating that there were no sectors where multiples whose peer groups were based on single valuation fundamentals produced the most accurate equity valuations. Also note that there is a

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[42] Note: The following six sectors were omitted for the construction of the PCA biplot: Banks, Beverages, Forestry and Paper, Media, Nonlife Insurance and Personal Goods. These six sectors contained missing data for certain PGVs and were consequently not included, i.e. only those sectors that contained values for each of the 10 PGVs were included.
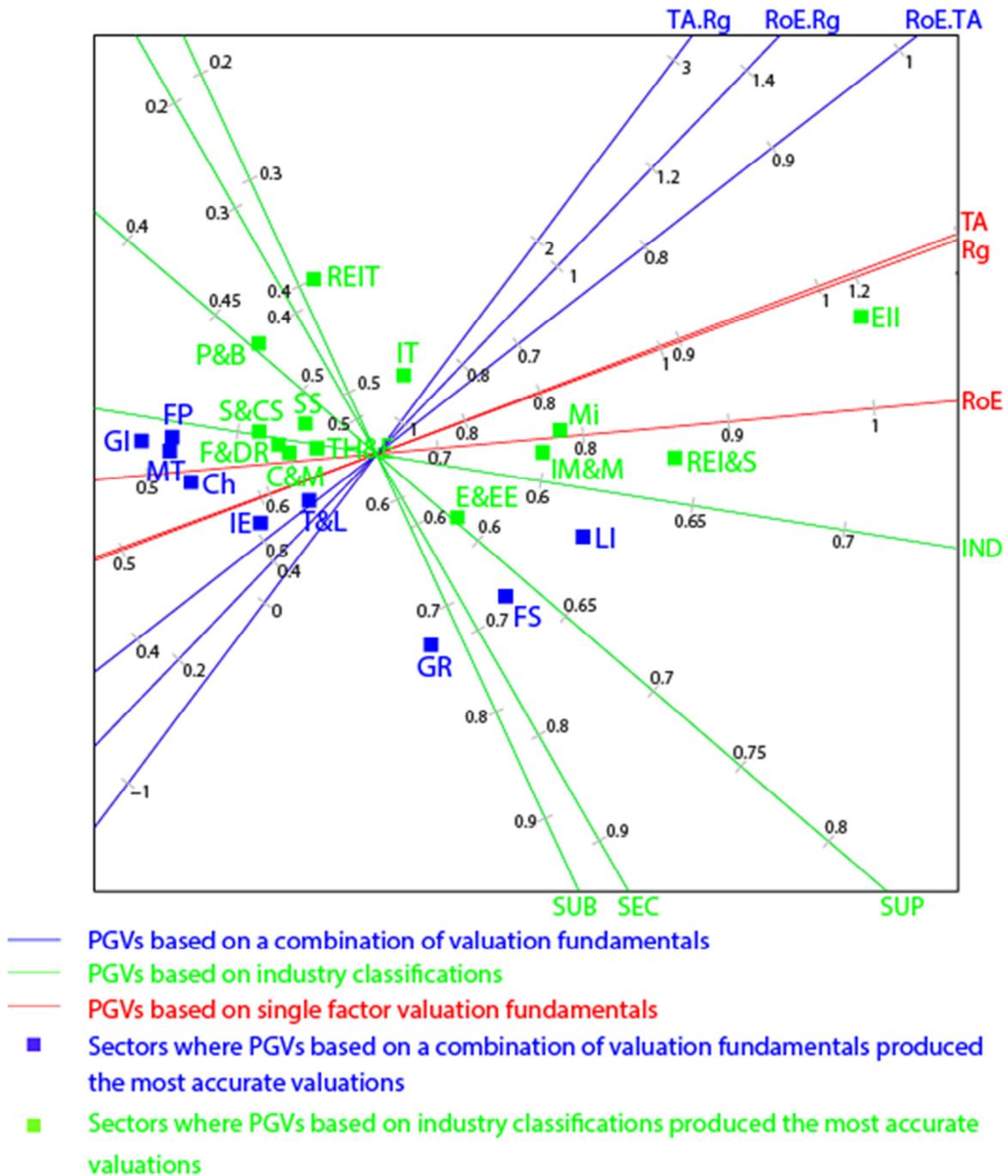
Figure 8.1: PCA biplot of the valuation performance of 10 PGVs over 22 sectors

fairly equal number of green and blue squares. On average, multiples whose peer groups were based on one of the four industry classifications produced the most accurate valuations for 13 of the sectors, compared to nine sectors where multiples whose peer groups were based on one of the three combinations of valuation fundamentals produced the most accurate valuations.

Also note from Figure 8.1 that each of the PGVs within each of the three PGV categories seems to be positively correlated. This is evident from the manner in which the differently coloured axes, green, blue and red, are grouped together. Note that the coloured axes depict the PGVs. The industry classifications are depicted as the green axes, while the blue and red axes depict the combinations of, and single, valuation fundamentals, respectively. A more accurate display of the correlations within each of the three PGV categories is depicted in the correlation monoplot in Figure 8.2.
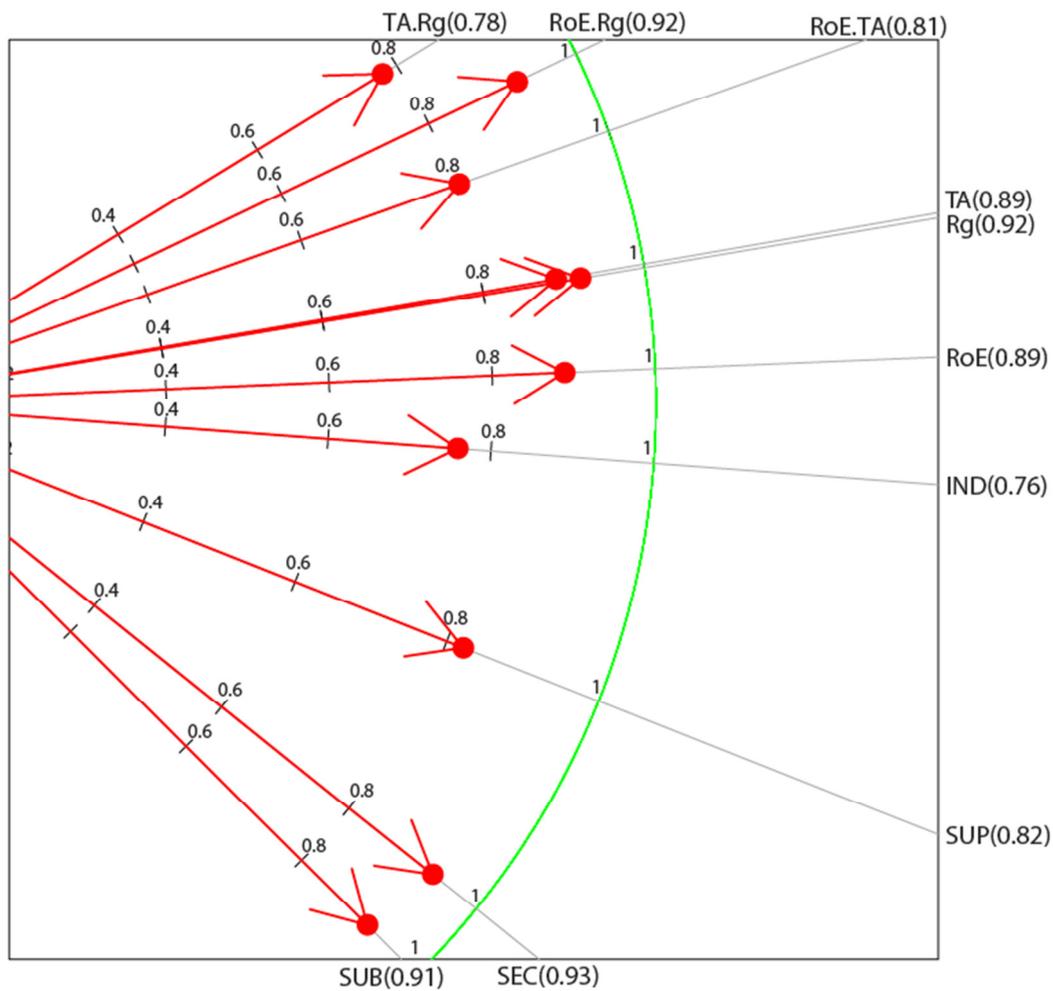
Figure 8.2: Correlation monoplot of the valuation performance of 10 PGVs over the 22 sectors contained in Table 8.2

All three combinations of valuation fundamentals are positively correlated. Equally evident is the strong positive correlation between TA and Rg, which essentially overlap, while RoE is located further away. This confirms the earlier findings in

Chapter 7, where TA and Rg produced equally poor results in terms of valuation accuracy, while RoE produced the most accurate valuations, compared to TA and Rg. Also evident from Figure 8.2 is how well correlated SEC and SUB are, relative to SUP and IND, which appear to be less well correlated. This confirms earlier findings from Chapter 4, where the most substantial increase in valuation accuracy occurred when narrowing the industry classification from IND to SEC, while further narrowing from SEC to SUB added little, if any, incremental valuation accuracy.

The approximations of the data points displayed in Figure 8.1, together with the actual data points, are contained in Table 8.2. The comparison between the actual and predicted data points over all 10 PGVs in Table 8.2 indicates that the loss in data accuracy is acceptable. The PCA quality reading was 74.91% and the PGV predictivity readings are contained in Table 8.3, confirming a moderate to low loss of data accuracy. The greatest loss in accuracy occurs with the IND PGV, with a reading of 57.60%.

8.5.2   A sector analysis of the valuation performance of multiples

From the results obtained in Section 8.5.1, it is now possible to identify an optimal PGV for each of the 28 sectors. Based on these 28 optimal PGVs, the valuation errors of 16 multiples are calculated and summarised in Table 8.4. However, given the multi-dimensional nature of the data in Table 8.4, it is difficult to assess the relative valuation performance of all 16 multiples across all 28 sectors. Consequently, an SVC was created in Table 8.5.

The SVC contained in Table 8.5 ranks the individual value drivers from left to right in order of valuation performance. The least accurate value driver in each sector is located to the far left of the SVC, while the most accurate value driver is located to the far right. For the Banking sector, for example, IC offers the least degree of valuation accuracy and HE offers the highest degree of valuation accuracy. As one moves from one value driver to the next most accurate value driver, i.e. from left to right in the SVC, the accompanying IMP.SVC reflects the improvement in valuation accuracy that each individual driver offers relative to the previous value driver on the

Table 8.2: PGVs: Actual and Predicted median valuation errors over 22 sectors

Sector	PGV									
	IND		SUP		SEC		SUB		RoE	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre	Act	Pre
Chemicals	0.4757	0.4877	0.5042	0.4895	0.5042	0.4778	0.5042	0.5136	0.5094	0.5296
Construction & Materials	0.5299	0.5177	0.5075	0.5133	0.5075	0.4967	0.5196	0.5255	0.5899	0.5986
Electronic & Electrical Equipment	0.5582	0.5751	0.5684	0.5865	0.6156	0.6111	0.6510	0.6351	0.6752	0.7090
Equity Investment Instruments	0.6763	0.6941	0.6731	0.6612	0.6731	0.6312	0.6731	0.6220	0.8395	0.9970
Financial Services	0.6109	0.5948	0.6493	0.6248	0.6493	0.6872	0.7043	0.7135	0.7628	0.7369
Food & Drug Retailers	0.5900	0.5138	0.6431	0.5075	0.4044	0.4866	0.4466	0.5156	0.5935	0.5917
Food Producers	0.4869	0.4792	0.4406	0.4706	0.4640	0.4382	0.4738	0.4722	0.5301	0.5196
General Industrials	0.4903	0.4696	0.5138	0.4616	0.4187	0.4283	0.4480	0.4641	0.4412	0.4984
General Retailers	0.6048	0.5734	0.6603	0.6142	0.6998	0.6916	0.6985	0.7248	0.6312	0.6829
Industrial Engineering	0.4761	0.5121	0.4861	0.5239	0.5875	0.5354	0.5950	0.5700	0.4933	0.5743
Industrial Metals & Mining	0.5507	0.5990	0.5684	0.5959	0.6176	0.5990	0.6342	0.6147	0.7983	0.7713
Industrial Transportation	0.5332	0.5504	0.5372	0.5287	0.5285	0.4880	0.4894	0.5062	0.6248	0.6814
Life Insurance	0.6523	0.6165	0.6393	0.6331	0.6540	0.6759	0.6540	0.6946	0.8759	0.7935
Mining	0.6043	0.6034	0.6087	0.5952	0.5851	0.5902	0.5510	0.6036	0.8466	0.7846
Mobile Telecommunications	0.4656	0.4792	0.4656	0.4737	0.4772	0.4470	0.4772	0.4820	0.5093	0.5170
Pharmaceuticals & Biotechnology	0.4253	0.5021	0.4437	0.4724	0.4173	0.4066	0.4173	0.4304	0.7102	0.5846
Real Estate Investment & Services	0.6554	0.6417	0.6179	0.6405	0.6376	0.6564	0.6376	0.6655	0.9813	0.8610
Real Estate Investment Trusts	0.6558	0.5164	0.5205	0.4720	0.3010	0.3827	0.3530	0.3998	0.6372	0.6263
Software & Computer Services	0.4866	0.5070	0.4866	0.4975	0.4902	0.4695	0.5023	0.4987	0.5632	0.5794
Support Services	0.4452	0.5212	0.4563	0.5101	0.4953	0.4823	0.5645	0.5085	0.6513	0.6112
Technology Hardware & Equipment	0.4533	0.5263	0.4533	0.5210	0.5145	0.5047	0.6194	0.5318	0.6282	0.6176
Travel & Leisure	0.5805	0.5265	0.4827	0.5333	0.4827	0.5388	0.6477	0.5696	0.5825	0.6089

Table 8.2…continued

Sector	PGV									
	TA		**Rg**		**RoE.TA**		**RoE.Rg**		**TA.Rg**	
	Act	**Pre**	**Act**	**Pre**	**Act**	**Pre**	**Act**	**Pre**	**Act**	**Pre**
Chemicals	0.4971	0.5597	0.5477	0.5334	0.4639	0.4871	0.4654	0.4019	0.4927	0.2354
Construction & Materials	0.6250	0.6285	0.6049	0.6318	0.5657	0.5466	0.5287	0.5324	0.6023	0.5984
Electronic & Electrical Equipment	0.7191	0.7181	0.8266	0.7608	0.6279	0.6038	0.6616	0.6326	0.6152	0.8100
Equity Investment Instruments	0.9368	1.0196	1.2093	1.1912	0.7153	0.8785	1.4236	1.2529	4.0008	2.5825
Financial Services	0.8351	0.7293	0.7227	0.7775	0.5260	0.5970	0.5226	0.5973	0.7327	0.6569
Food & Drug Retailers	0.6072	0.6236	0.5749	0.6246	0.4667	0.5443	0.4934	0.5297	0.5406	0.5974
Food Producers	0.5362	0.5587	0.5627	0.5315	0.4403	0.4951	0.4628	0.4304	0.5447	0.3442
General Industrials	0.5160	0.5386	0.4759	0.5027	0.4380	0.4787	0.4174	0.3956	0.5651	0.2507
General Retailers	0.6169	0.6708	0.6231	0.6940	0.5431	0.5418	0.5223	0.4704	0.5028	0.2886
Industrial Engineering	0.6173	0.5933	0.6038	0.5819	0.5018	0.5052	0.4392	0.4281	0.7164	0.2719
Industrial Metals & Mining	0.8367	0.7874	0.8029	0.8594	0.6993	0.6707	0.8670	0.7880	1.0287	1.2655
Industrial Transportation	0.6897	0.7188	0.6888	0.7604	0.7721	0.6321	0.7592	0.7294	0.9569	1.1716
Life Insurance	0.6582	0.7922	1.0969	0.8672	0.6278	0.6579	0.7009	0.7387	0.6080	1.0718
Mining	0.8969	0.8036	0.8074	0.8824	0.8215	0.6876	0.6479	0.8290	0.7445	1.3895
Mobile Telecommunications	0.5568	0.5538	0.5486	0.5246	0.4085	0.4886	0.4398	0.4133	0.6718	0.2889
Pharmaceuticals & Biotechnology	0.7286	0.6355	0.7071	0.6407	0.5939	0.5734	0.4544	0.6169	0.6416	0.9025
Real Estate Investment & Services	0.9466	0.8688	0.9251	0.9762	0.8090	0.7331	0.7904	0.9153	0.8883	1.5932
Real Estate Investment Trusts	0.6709	0.6857	0.6968	0.7121	0.6053	0.6252	0.6839	0.7412	0.7342	1.2764
Software & Computer Services	0.6364	0.6147	0.5757	0.6117	0.5887	0.5399	0.5075	0.5243	0.6144	0.5932
Support Services	0.6115	0.6454	0.7542	0.6557	0.5592	0.5655	0.7237	0.5791	0.5179	0.7427
Technology Hardware & Equipment	0.6332	0.6468	0.6649	0.6578	0.6204	0.5617	0.6300	0.5647	0.7976	0.6859
Travel & Leisure	0.6498	0.6292	0.5906	0.6332	0.5573	0.5377	0.4708	0.5012	0.5800	0.4800

Table 8.3: Predictivity readings of 10 PGVs

PGV	IND	SUP	SEC	SUB	RoE	TA	Rg	RoE.Rg	RoE.TA	TA.Rg
Predictivity	0.5760	0.6750	0.8690	0.8350	0.7900	0.7940	0.8470	0.8470	0.6500	0.6080

SVC. In the case of the Banking sector, for example, TA offers 4.84% more accurate valuations than IC, while, at 0.76%, NCIfIA offers only marginally more accurate valuations than EBIT. The total of all these incremental improvements in the banking sector adds up to an IMP.SVC of 116.52%. Note that the comparative basis for calculating the incremental IMP, as one moves from left to right in Table 8.5, does not remain constant. Whereas the 4.84% IMP is calculated based on the IC valuation error basis of 0.7823, the next IMP of 0.76% is based on the TA valuation error basis of 0.7444. The effect of the continuously changing basis (base effect) overestimates the opportunity costs. If the base effect in the banking sector, for example, is eliminated, HE produced valuations that are 71.28% more accurate than those produced by IC. The cells with no IMP.SVC are either the worst performing value drivers in a particular sector, such as IC in the Banking sector, for example, or reflect multiples for which there were no values and that were subsequently not allocated a rank.

The following can be gleaned from the SVC in Table 8.5:

Firstly, earnings-based value drivers generally offer the greatest degree of valuation accuracy across all 28 sectors. This is evident from the fact that earnings-based value drivers are the highest ranked value drivers in 21 (75.00%) of the sectors. Asset-based value drivers offer the highest degree of valuation accuracy over 5 (17.86%) of the sectors, while revenue- and cash flow-based value drivers offer the greatest degree of valuation accuracy in only one (3.57%) sector each. OD failed to produce the most accurate valuation in any of the sectors.

The multi-dimensional nature of the data contained in Tables 8.4 and 8.5 necessitates the use of a PCA biplot to ease comparison. The PCA biplot in Figure 8.3 displays the data contained in Tables 8.4 and 8.5 in the best possible two-dimensional space, effectively reducing the multi-dimensional nature of the data. The relative valuation performance of the 16 multiples over all 22 sectors, as contained in Tables 8.4 and 8.5, is immediately evident from Figure 8.3. Each of the 22 sectors is colour-coded according to the most accurate value driver category in each sector. The dominance of earnings-based value drivers (blue squares) is evident, as they dominate the two-dimensional space. The red squares depict the three sectors

Table 8.4: Average median valuation errors per sector for 16 multiples

	GP	EBITDA	EBIT	PAT	PBT	HE	TA	IC	BVE	R	CgbO	NCIfOA	NCIfIA	OD	FCFE	FCFF	PGV
Banks	NA	0.6634	0.6900	0.3459	0.3268	0.2247	0.7444	0.7823	0.2637	NA	0.4224	0.6088	0.6848	0.2878	0.6027	0.4932	SUP3
Beverages	NA	0.4017	0.3258	0.4158	0.3752	0.2154	0.5715	0.5536	NA	NA	NA	NA	NA	0.2563	NA	NA	SUP
Chemicals	0.4150	0.2928	0.2921	0.2723	0.2897	0.2939	0.4411	0.4243	0.3031	0.5376	0.3282	0.6858	1.0411	0.3977	0.7734	0.6343	RoE.TA
Construction & Materials	0.7122	0.4131	0.3772	0.3821	0.3374	0.2937	0.4703	0.5160	0.6044	0.4787	0.4696	0.5743	0.6749	0.4838	0.6863	0.6458	SUP2
Electronic & Electrical Equipment	0.6382	0.5344	0.5050	0.4769	0.4831	0.3246	0.6448	0.6615	0.6391	0.6684	0.5334	0.5127	0.5675	0.6335	0.5545	0.5532	IND
Equity Investment Instruments	0.6620	0.6823	0.6477	0.6960	0.6788	0.5390	0.6203	0.6556	0.6697	0.6850	0.6239	0.7240	0.7267	0.6754	0.6319	0.8511	SUP3
Financial Services	0.7166	0.3286	0.2708	0.4008	0.3633	0.3119	0.5030	0.6764	0.3217	0.8905	0.4869	0.5609	0.5811	0.5508	0.7018	0.6965	RoE.Rg
Food & Drug Retailers	0.3468	0.3423	0.2706	0.3014	0.2806	0.1612	0.3416	0.3619	0.7069	0.2775	0.2759	0.5262	0.8195	0.3594	0.6576	0.4408	SEC
Food Producers	0.4272	0.3086	0.2907	0.3536	0.2931	0.2525	0.4327	0.4740	0.3126	0.4549	0.3490	0.5654	0.8657	0.3390	0.7303	0.5962	RoE.TA
Forestry & Paper	0.5791	0.4188	0.5696	0.6753	0.6372	0.1314	0.1393	0.1470	0.1083	0.3096	0.5716	0.8063	1.5379	0.4978	0.8414	0.4697	RoE.TA
General Industrials	0.3890	0.2860	0.2524	0.2328	0.2201	0.2163	0.3354	0.3334	0.2712	0.3962	0.3110	0.2945	1.1132	0.3716	0.9510	0.7053	RoE.Rg
General Retailers	0.6238	0.3812	0.3517	0.3065	0.3050	0.2229	0.5347	0.5850	0.5644	0.6374	0.4517	0.5088	0.8691	0.3279	0.7325	0.6428	TA.Rg
Industrial Engineering	0.4840	0.2750	0.2799	0.2176	0.3326	0.2804	0.3463	0.3118	0.2357	0.3332	0.3165	0.5463	1.0842	0.4083	0.8884	0.6863	RoE.Rg
Industrial Metals & Mining	0.5785	0.4300	0.5116	0.5965	0.5625	0.5882	0.5069	0.5620	0.5868	0.5531	0.4886	0.6747	0.5675	0.5341	0.5056	0.5642	IND
Industrial Transportation	0.6629	0.4327	0.3831	0.4524	0.5177	0.3382	0.5114	0.5228	0.4807	0.4001	0.4438	0.5380	NA	0.3413	NA	0.8263	SUB
Life Insurance	0.5680	0.4783	0.4269	0.3281	0.4095	0.3393	0.4921	0.4831	0.2957	0.7665	0.7246	0.7576	1.5356	0.7292	0.7097	0.6841	TA.Rg
Media	0.6291	0.5294	0.5396	0.4299	0.4263	0.3672	0.5935	0.6288	0.2923	0.7066	0.5565	0.4983	0.8088	0.5079	0.7014	0.5881	RoE.TA
Mining	0.5704	0.4332	0.4615	0.4263	0.4592	0.4737	0.5287	0.5621	0.6141	0.4359	0.4779	0.5034	0.7492	0.6780	0.7493	0.6926	SUB
Mobile Telecommunications	0.6148	0.2458	0.2555	0.3596	0.2849	0.1501	0.4854	0.5061	0.3801	0.4712	0.2745	0.6222	0.9284	0.3036	0.3927	0.2623	RoE.TA
Non-life Insurance	0.3311	0.4082	0.4402	0.3960	0.3618	0.3787	0.5148	0.6147	0.4394	0.3311	0.4460	0.5002	0.4020	0.5766	0.8281	0.5634	SEC
Personal Goods	0.4045	0.4523	0.4310	0.7157	0.5136	0.2919	0.4813	0.5862	0.6171	0.6375	0.4140	0.3271	0.9620	0.6838	0.6373	0.2148	TA.Rg
Pharmaceuticals & Biotechnology	0.5719	0.3197	0.3687	0.3319	0.3523	0.3099	0.2818	0.3586	0.7178	0.5837	0.4094	0.4013	NA	NA	NA	NA	SEC
Real Estate Investment & Services	0.6193	0.4165	0.4165	0.7072	0.7380	0.3210	0.4884	0.4414	0.6618	0.7279	0.4140	0.7717	0.8921	0.9904	0.7289	0.5507	SUP
Real Estate Investment Trusts	0.2008	0.2156	0.2053	0.2702	0.2557	0.2233	0.2367	0.2524	0.1363	0.2008	0.2083	0.7493	NA	0.2566	0.6515	0.4531	SEC
Software & Computer Services	0.5824	0.4192	0.3451	0.3351	0.3242	0.2605	0.6491	0.6783	0.6175	0.6653	0.4170	0.4712	0.6324	0.5042	0.4791	0.4045	SUP
Support Services	0.4728	0.3498	0.3259	0.2981	0.3032	0.2974	0.4267	0.4745	0.4841	0.5729	0.3954	0.4069	0.6773	0.5537	0.5933	0.4917	IND
Technology Hardware & Equipment	0.5430	0.2636	0.3913	0.2233	0.2299	0.2497	0.5175	0.6001	0.4927	0.7207	0.5595	0.4860	NA	NA	NA	0.6160	SUP
Travel & Leisure	0.5886	0.3574	0.3181	0.3115	0.2686	0.2942	0.5440	0.5278	0.3718	0.6715	0.3222	0.4706	1.0239	0.3038	0.7495	0.4098	RoE.Rg

Note: The PGV in the far right column indicates the variable that was employed for each particular sector. The number references in the PGV column indicate the number of industry classifications that reflected similar valuation errors. The reference SUP3 in the Banking sector, for example, indicates that all three industry classifications including, and below SUP, namely SUP, SEC and SUB, exhibited the same valuation error.

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Table 8.5: Sector Value Chain (SVC)

	Ranking																Cumulative
	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	IMP.SVC
Banks																	
Value driver	R	GP	IC	TA	EBIT	NCIfIA	EBITDA	NCIfOA	FCFE	FCFF	CgbO	PAT	PBT	OD	BVE	HE	
IMP.SVC				4.84%	7.31%	0.76%	3.13%	8.23%	0.99%	18.18%	14.35%	18.12%	5.52%	11.92%	8.37%	14.79%	116.52%
Beverages																	
Value driver	FCFF	FCFE	NCIfIA	NCIfOA	CgbO	R	BVE	GP	TA	IC	PAT	EBITDA	PBT	EBIT	OD	HE	
IMP.SVC										3.13%	24.89%	3.40%	6.59%	13.17%	21.35%	15.94%	88.47%
Chemicals																	
Value driver	NCIfIA	FCFE	NCIfOA	FCFF	R	TA	IC	GP	OD	CgbO	BVE	HE	EBITDA	EBIT	PBT	PAT	
IMP.SVC		25.71%	11.33%	7.52%	15.24%	17.96%	3.80%	2.19%	4.18%	17.47%	7.66%	3.02%	0.37%	0.24%	0.82%	6.01%	123.51%
Construction & Materials																	
Value driver	GP	FCFE	NCIfIA	FCFF	BVE	NCIfOA	IC	OD	R	TA	CgbO	EBITDA	PAT	EBIT	PBT	HE	
IMP.SVC		3.64%	1.66%	4.32%	6.41%	4.97%	10.15%	6.24%	1.06%	1.75%	0.14%	12.04%	7.49%	1.30%	10.54%	12.95%	84.67%
Electronic & Electrical Equipment																	
Value driver	R	IC	TA	BVE	GP	OD	NCIfIA	FCFE	FCFF	EBITDA	CgbO	NCIfOA	EBIT	PBT	PAT	HE	
IMP.SVC		1.03%	2.52%	0.88%	0.15%	0.74%	10.41%	2.29%	0.24%	3.39%	0.19%	3.88%	1.50%	4.35%	1.27%	31.94%	64.79%
Equity Investment Instruments																	
Value driver	FCFF	NCIfIA	NCIfOA	PAT	R	EBITDA	PBT	OD	BVE	GP	IC	EBIT	FCFE	CgbO	TA	HE	
IMP.SVC		14.61%	0.37%	3.87%	1.58%	0.39%	0.51%	0.50%	0.84%	1.16%	0.96%	1.21%	2.44%	1.27%	0.58%	13.11%	43.40%
Financial Services																	
Value driver	R	GP	FCFE	FCFF	IC	NCIfIA	NCIfOA	OD	TA	CgbO	PAT	PBT	EBITDA	BVE	HE	EBIT	
IMP.SVC		19.53%	2.07%	0.75%	2.89%	14.08%	3.48%	1.79%	8.68%	3.21%	17.69%	9.36%	9.54%	2.12%	3.03%	13.18%	111.40%
Food & Drug Retailers																	
Value driver	NCIfIA	BVE	FCFE	NCIfOA	FCFF	IC	OD	GP	EBITDA	TA	PAT	PBT	R	CgbO	EBIT	HE	
IMP.SVC		13.74%	6.97%	19.99%	16.22%	17.90%	0.69%	3.52%	1.28%	0.20%	11.77%	6.90%	1.10%	0.58%	1.92%	40.43%	143.22%
Food Producers																	
Value driver	NCIfIA	FCFE	FCFF	NCIfOA	IC	R	TA	GP	PAT	CgbO	OD	BVE	EBITDA	PBT	EBIT	HE	
IMP.SVC		15.64%	18.36%	5.17%	16.16%	4.03%	4.88%	1.28%	17.22%	1.30%	2.87%	7.80%	1.26%	5.02%	0.82%	13.14%	114.96%
Forestry & Paper																	
Value driver	NCIfIA	FCFE	NCIfOA	PAT	PBT	GP	CgbO	EBIT	OD	FCFF	EBITDA	R	IC	TA	HE	BVE	
IMP.SVC		45.29%	4.17%	16.25%	5.64%	9.12%	1.30%	0.34%	12.61%	5.64%	10.85%	26.08%	52.51%	5.24%	5.71%	17.59%	218.33%

Table 8.5…continued

							Ranking										Cumulative
	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	IMP.SVC
General Industrials																	
Value driver	NCIfIA	FCFE	FCFF	R	GP	OD	TA	IC	CgbO	NCIfOA	EBITDA	BVE	EBIT	PAT	PBT	HE	
IMP.SVC		14.57%	25.84%	43.82%	1.82%	4.47%	9.74%	0.60%	6.72%	5.32%	2.89%	5.18%	6.91%	7.77%	5.46%	1.73%	142.82%
General Retailers																	
Value driver	NCIfIA	FCFE	FCFF	R	GP	IC	BVE	TA	NCIfOA	CgbO	EBITDA	EBIT	OD	PAT	PBT	HE	
IMP.SVC		15.71%	12.25%	0.84%	2.13%	6.22%	3.53%	5.26%	4.83%	11.23%	15.60%	7.75%	6.75%	6.53%	0.49%	26.92%	126.05%
Industrial Engineering																	
Value driver	NCIfIA	FCFE	FCFF	NCIfOA	GP	OD	TA	R	PBT	CgbO	IC	HE	EBIT	EBITDA	BVE	PAT	
IMP.SVC		18.06%	22.75%	20.40%	11.40%	15.64%	15.18%	3.78%	0.18%	4.84%	1.48%	10.07%	0.18%	1.75%	14.29%	7.68%	147.70%
Industrial Metals & Mining																	
Value driver	NCIfOA	PAT	HE	BVE	GP	NCIfIA	FCFF	PBT	IC	R	OD	EBIT	TA	FCFE	CgbO	EBITDA	
IMP.SVC		11.60%	1.38%	0.24%	1.41%	1.90%	0.58%	0.30%	0.10%	1.57%	3.44%	4.21%	0.92%	0.26%	3.36%	11.99%	43.27%
Industrial Transportation																	
Value driver	FCFE	NCIfIA	FCFF	GP	NCIfOA	IC	PBT	TA	BVE	PAT	CgbO	EBITDA	R	EBIT	OD	HE	
IMP.SVC				19.77%	18.84%	2.83%	0.97%	1.23%	5.99%	5.89%	1.90%	2.50%	7.53%	4.25%	10.91%	0.91%	83.53%
Life Insurance																	
Value driver	NCIfIA	R	NCIfOA	OD	CgbO	FCFE	FCFF	GP	TA	IC	EBITDA	EBIT	PBT	HE	PAT	BVE	
IMP.SVC		50.08%	1.16%	3.75%	0.63%	2.06%	3.61%	16.97%	13.36%	1.83%	0.99%	10.75%	4.08%	17.14%	3.30%	9.88%	139.59%
Media																	
Value driver	NCIfIA	R	FCFE	GP	IC	TA	FCFF	CgbO	EBIT	EBITDA	OD	NCIfOA	PAT	PBT	HE	BVE	
IMP.SVC		12.63%	0.74%	10.31%	0.05%	5.61%	0.91%	5.37%	3.04%	1.89%	4.06%	1.89%	13.73%	0.84%	13.86%	20.40%	95.32%
Mining																	
Value driver	FCFE	NCIfIA	FCFF	OD	BVE	GP	IC	TA	NCIfOA	CgbO	HE	EBIT	PBT	R	EBITDA	PAT	
IMP.SVC		0.01%	7.55%	2.11%	9.42%	7.12%	1.46%	5.95%	4.79%	5.06%	0.88%	2.58%	0.50%	5.08%	0.61%	1.59%	54.70%
Mobile Telecommunications																	
Value driver	NCIfIA	NCIfOA	GP	IC	TA	R	FCFE	BVE	PAT	OD	PBT	CgbO	FCFF	EBIT	EBITDA	HE	
IMP.SVC		32.99%	1.19%	17.67%	4.10%	2.92%	16.67%	3.21%	5.39%	15.56%	6.18%	3.65%	4.43%	2.59%	3.82%	38.94%	159.30%
Non-life Insurance																	
Value driver	FCFE	IC	OD	FCFF	TA	NCIfOA	CgbO	EBIT	BVE	EBITDA	NCIfIA	PAT	HE	PBT	GP	R	
IMP.SVC		25.78%	6.19%	2.29%	8.64%	2.83%	10.84%	1.30%	0.18%	7.10%	1.52%	1.49%	4.37%	4.46%	8.49%	0.00%	85.46%

Table 8.5…continued

							Ranking										Cumulative
	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	IMP.SVC
							Personal Goods										
Value driver	NCIfIA	PAT	OD	R	FCFE	BVE	IC	PBT	TA	EBITDA	EBIT	CgbO	GP	NCIfOA	HE	FCFF	
IMP.SVC		25.61%	4.45%	6.78%	0.02%	3.17%	5.01%	12.39%	6.28%	6.04%	4.71%	3.94%	2.28%	19.13%	10.76%	26.41%	136.99%
							Pharmaceuticals & Biotechnology										
Value driver	FCFF	FCFE	OD	NCIfIA	BVE	R	GP	CgbO	NCIfOA	EBIT	IC	PBT	PAT	EBITDA	HE	TA	
IMP.SVC						18.68%	2.02%	28.41%	1.98%	8.12%	2.74%	1.76%	5.79%	3.68%	3.07%	9.07%	85.32%
							Real Estate Investment & Services										
Value driver	OD	NCIfIA	NCIfOA	PBT	FCFE	R	PAT	BVE	GP	FCFF	TA	IC	EBITDA	EBIT	CgbO	HE	
IMP.SVC		9.93%	13.50%	4.36%	1.23%	0.14%	2.84%	6.42%	6.42%	11.08%	11.31%	9.62%	5.64%	0.00%	0.60%	22.46%	105.56%
							Real Estate Investment Trusts										
Value driver	NCIfIA	NCIfOA	FCFE	FCFF	PAT	OD	PBT	IC	TA	HE	EBITDA	CgbO	EBIT	GP	R	BVE	
IMP.SVC			13.05%	30.46%	40.36%	5.03%	0.37%	1.27%	6.22%	5.66%	3.45%	3.41%	1.44%	2.17%	0.00%	32.12%	145.02%
							Software & Computer Services										
Value driver	IC	R	TA	NCIfIA	BVE	GP	OD	FCFE	NCIfOA	EBITDA	CgbO	FCFF	EBIT	PAT	PBT	HE	
IMP.SVC		1.92%	2.43%	2.57%	2.36%	5.68%	13.44%	4.98%	1.64%	11.05%	0.52%	3.00%	14.69%	2.88%	3.25%	19.65%	90.06%
							Support Services										
Value driver	NCIfIA	FCFE	R	OD	FCFF	BVE	IC	GP	TA	NCIfOA	CgbO	EBITDA	EBIT	PBT	PAT	HE	
IMP.SVC		12.40%	3.45%	3.34%	11.21%	1.54%	1.99%	0.36%	9.74%	4.65%	2.83%	11.52%	6.83%	6.97%	1.68%	0.23%	78.74%
							Technology Hardware & Equipment										
Value driver	FCFE	OD	NCIfIA	R	FCFF	IC	CgbO	GP	TA	BVE	NCIfOA	EBIT	EBITDA	HE	PBT	PAT	
IMP.SVC					14.53%	2.59%	6.76%	2.95%	4.71%	4.79%	1.36%	19.48%	32.65%	5.26%	7.93%	2.87%	105.86%
							Travel & Leisure										
Value driver	NCIfIA	FCFE	R	GP	TA	IC	NCIfOA	FCFF	BVE	EBITDA	CgbO	EBIT	PAT	OD	HE	PBT	
IMP.SVC		26.80%	10.41%	12.35%	7.57%	2.98%	10.84%	12.92%	9.27%	3.87%	9.85%	1.29%	2.08%	2.47%	3.14%	8.70%	124.54%
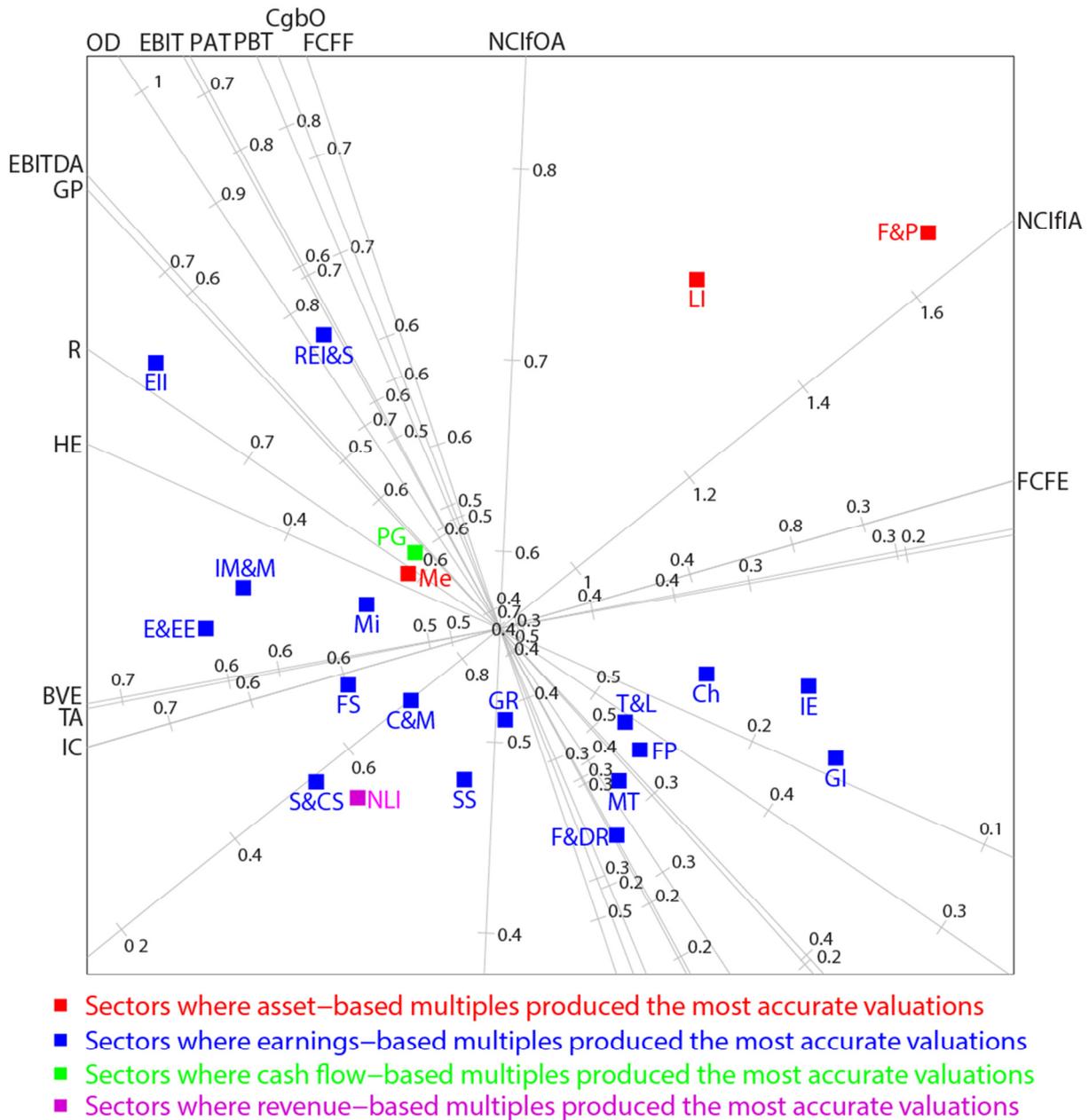
Figure 8.3: PCA biplot of the valuation performance of the 16 multiples over over the 22 sectors contained in Table 8.2

where asset-based value drivers produced the most accurate valuations, namely Forestry and Paper, Life Insurance and Media. Cash flow- (green square) and revenue-based (pink square) value drivers produced the most accurate valuation in one sector each, namely Personal Goods and Nonlife Insurance. Note that there were no dark green squares, indicating that OD did not produce the most accurate valuation in any of the sectors.

In order to gain a clearer perspective of the correlations between the 16 value drivers over the 22 sectors, a correlation monoplot is depicted in Figure 8.4.
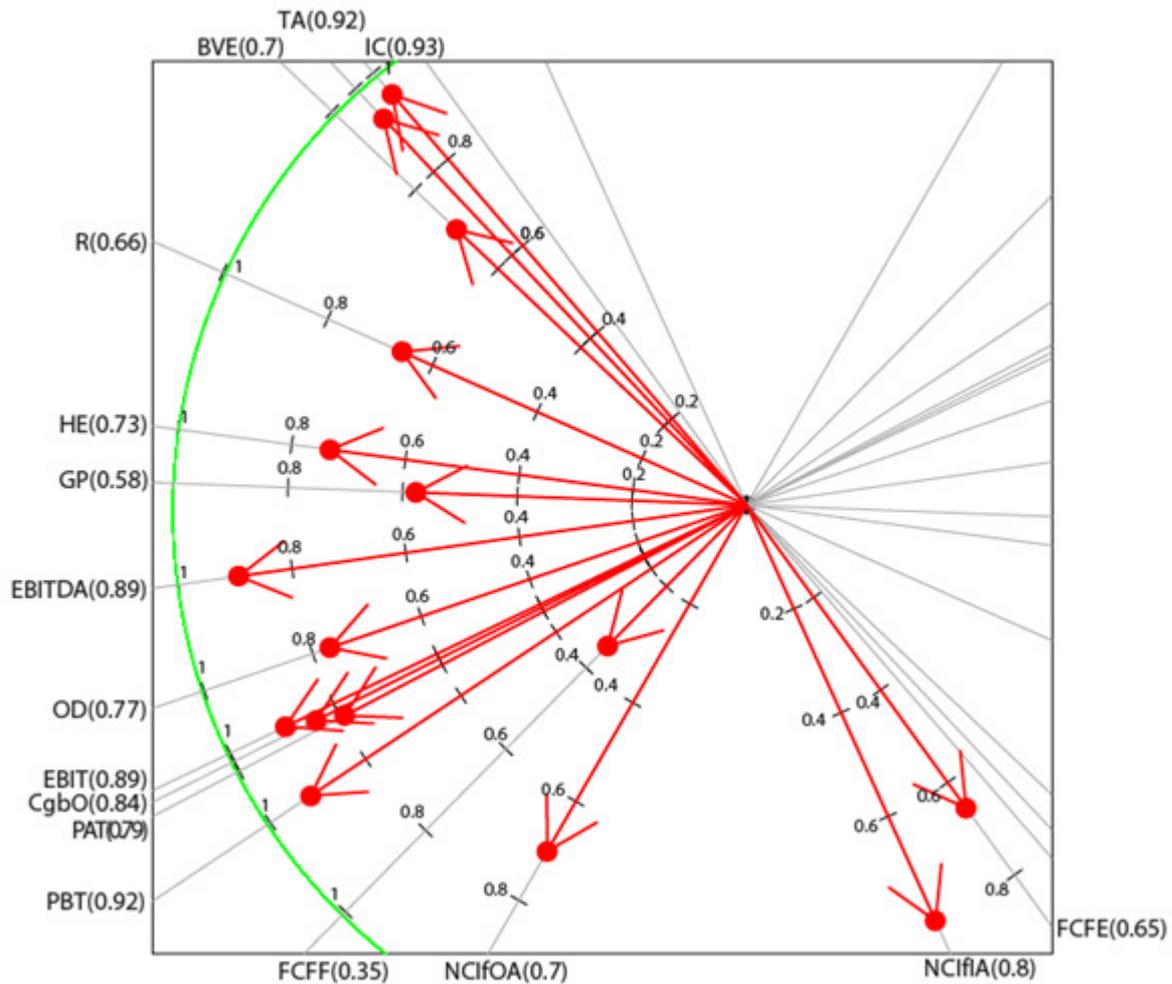
Figure 8.4: Correlation monoplot of the valuation performance of the 16 multiples over the 22 sectors contained in Table 8.2

Note how the value drivers from each value driver category cluster together. In the top left quadrant the asset-based value drivers are clustered together, suggesting a highly positive correlation among these three value drivers. Similarly, the middle and lower left quadrants are occupied by earnings-based value drivers (HE to PBT). However, cash flow-based value drivers seem to offer a mixed bag in terms of correlations. Although CgbO, FCFF and NCIfOA seem fairly positively correlated, NCIfIA's position is almost orthogonal to CgbO, for example, suggesting an almost zero correlation, while FCFE's position relative to CgbO shows a negative correlation.

Note that the revenue- and dividend-based value driver categories each contain only one value driver and therefore a correlation analysis is nonsensical in these cases. It is also of interest to note how the positive correlations between the respective value driver categories decline and even become negative as one moves anti-clockwise from the asset-based value drivers, in the top left quadrant, through the earnings-based value drivers, positioned in the middle and lower left quadrants, and then on to the lower right quadrant. This may suggest that the various value drivers carry incremental information content, which is an important consideration when compiling composite multiples.

The approximations and the actual data points of the PCA biplot in Figure 8.3 are contained in Table 8.6. The comparison between the actual and predicted data points over all 16 value drivers in Table 8.6 indicates that the loss in data accuracy is acceptable. The PCA quality reading was 62.52%, and the majority of the predictivity readings of the multiples contained in Table 8.7 indicate a moderate to low loss of data accuracy. However, five multiples indicate a low reading, reflecting a substantial loss of data, namely GP (29.10%), R (33.90%), FCFE (31.70%) and FCFF (5.70%).

Secondly, on an individual value driver basis, the earnings-based value driver HE is the highest overall ranked individual value driver, producing the most accurate valuations in 14 (50.00%) of the sectors. PAT, another earnings-based value driver, and the asset-based value driver BVE each produced the most accurate valuations in four (10.71%) of the sectors. EBIT, EBITDA, FCFF, TA, R and PBT each achieved the highest degree of valuation accuracy in one sector.

Thirdly, a sub-optimal choice of value driver could carry a substantial opportunity cost. The cumulative IMP.SVC in the SVC in Table 8.5 ranges from 43.27% to 218.33% and, with the exception of the Equity Investment Instruments and Industrial Metals and Mining sectors, all of the other sectors carry opportunity costs of more than 50%, which is substantial. The majority (57.14%) of the sectors indicate cumulative IMP.SVCs in excess of 100%.

Table 8.6: Multiples: Actual and Predicted valuation errors over 22 sectors

Sector	Multiple							
	GP		EBITDA		EBIT		PAT	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre
Chemicals	0.4150	0.4878	0.2928	0.3239	0.2921	0.3197	0.2723	0.3233
Construction & Materials	0.7122	0.5457	0.4131	0.4016	0.3772	0.3794	0.3821	0.4038
Electronic & Electrical Equipment	0.6382	0.6072	0.5344	0.4853	0.5050	0.4612	0.4769	0.5156
Equity Investment Instruments	0.6620	0.6806	0.6823	0.5871	0.6477	0.5919	0.6960	0.6960
Financial Services	0.7166	0.5629	0.3286	0.4251	0.2708	0.4015	0.4008	0.4339
Food & Drug Retailers	0.3468	0.4692	0.3423	0.2971	0.2706	0.2692	0.3014	0.2528
Food Producers	0.4272	0.4844	0.3086	0.3185	0.2907	0.3019	0.3536	0.2982
Forestry & Paper	0.5791	0.5437	0.4188	0.4038	0.5696	0.4630	0.6753	0.5231
General Industrials	0.3890	0.4399	0.2860	0.2583	0.2524	0.2507	0.2328	0.2287
General Retailers	0.6238	0.5207	0.3812	0.3677	0.3517	0.3479	0.3065	0.3609
Industrial Engineering	0.4840	0.4628	0.2750	0.2900	0.2799	0.2895	0.2176	0.2822
Industrial Metals & Mining	0.5785	0.6087	0.4300	0.4879	0.5116	0.4705	0.5965	0.5287
Life Insurance	0.5680	0.5828	0.4783	0.4561	0.4269	0.4982	0.3281	0.5701
Media	0.6291	0.5762	0.5294	0.4442	0.5396	0.4368	0.4299	0.4832
Mining	0.5704	0.5780	0.4332	0.4462	0.4615	0.4331	0.4263	0.4778
Mobile Telecommunications	0.6148	0.4816	0.2458	0.3144	0.2555	0.2931	0.3596	0.2859
Nonlife Insurance	0.3311	0.5343	0.4082	0.3853	0.4402	0.3488	0.3960	0.3612
Personal Goods	0.4045	0.5797	0.4523	0.4491	0.4310	0.4446	0.7157	0.4939
Real Estate Investment & Services	0.6193	0.6507	0.4165	0.5471	0.4165	0.5637	0.7072	0.6581
Software & Computer Services	0.5824	0.5470	0.4192	0.4026	0.3451	0.3659	0.3351	0.3845
Support Services	0.4728	0.5154	0.3498	0.3600	0.3259	0.3311	0.2981	0.3373
Travel & Leisure	0.5886	0.4941	0.3574	0.3319	0.3181	0.3179	0.3115	0.3202

Table 8.6…continued

Sector	Multiple							
	PBT		HE		TA		IC	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre
Construction & Materials	0.2897	0.3151	0.2939	0.2273	0.4411	0.3927	0.4243	0.4067
Electronic & Electrical Equipment	0.3374	0.3798	0.2937	0.3287	0.4703	0.5228	0.5160	0.5682
Equity Investment Instruments	0.4831	0.4856	0.3246	0.4139	0.6448	0.6054	0.6615	0.6662
Food & Drug Retailers	0.6788	0.6780	0.5390	0.4751	0.6203	0.6043	0.6556	0.6514
Industrial Metals & Mining	0.3633	0.4078	0.3119	0.3537	0.5030	0.5486	0.6764	0.5992
Industrial Transportation	0.2806	0.2315	0.1612	0.2330	0.3416	0.4454	0.3619	0.4797
Mining	0.2931	0.2827	0.2525	0.2388	0.4327	0.4281	0.4740	0.4540
Pharmaceuticals & Biotechnology	0.6372	0.5493	0.1314	0.2199	0.1393	0.2590	0.1470	0.2199
Real Estate Investment & Services	0.2201	0.2221	0.2163	0.1672	0.3354	0.3440	0.3334	0.3510
Real Estate Investment Trusts	0.3050	0.3405	0.2229	0.2918	0.5347	0.4837	0.5850	0.5210
Software & Computer Services	0.3326	0.2783	0.2804	0.1888	0.3463	0.3496	0.3118	0.3543
Support Services	0.5625	0.5028	0.5882	0.4072	0.5069	0.5856	0.5620	0.6398
Technology Hardware & Equipment	0.4095	0.5826	0.3393	0.2951	0.4921	0.3631	0.4831	0.3504
Chemicals	0.4263	0.4660	0.3672	0.3505	0.5935	0.5131	0.6288	0.5499
Financial Services	0.4592	0.4569	0.4737	0.3603	0.5287	0.5338	0.5621	0.5768
Food Producers	0.2849	0.2676	0.1501	0.2412	0.4854	0.4398	0.5061	0.4700
General Industrials	0.3618	0.3294	0.3787	0.3319	0.5148	0.5543	0.6147	0.6118
General Retailers	0.5136	0.4782	0.2919	0.3514	0.4813	0.5084	0.5862	0.5429
Industrial Engineering	0.7380	0.6497	0.3210	0.4195	0.4884	0.5292	0.4414	0.5576
Life Insurance	0.3242	0.3516	0.2605	0.3493	0.6491	0.5708	0.6783	0.6314
Mobile Telecommunications	0.3032	0.3117	0.2974	0.2967	0.4267	0.5066	0.4745	0.5522
Travel & Leisure	0.2686	0.3055	0.2942	0.2486	0.5440	0.4321	0.5278	0.4576

Table 8.6…continued

Sector	Multiple							
	BVE		R		CgbO		NCIfOA	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre
Construction & Materials	0.3031	0.3369	0.5376	0.4613	0.3282	0.3788	0.6858	0.5406
Electronic & Electrical Equipment	0.6044	0.5220	0.4787	0.5703	0.4696	0.4201	0.5743	0.5198
Equity Investment Instruments	0.6391	0.6402	0.6684	0.6706	0.5334	0.4925	0.5127	0.5527
Food & Drug Retailers	0.6697	0.6405	0.6850	0.7625	0.6239	0.6298	0.7240	0.6903
Industrial Metals & Mining	0.3217	0.5589	0.8905	0.5992	0.4869	0.4391	0.5609	0.5265
Industrial Transportation	0.7069	0.4107	0.2775	0.4527	0.2759	0.3172	0.5262	0.4540
Mining	0.3126	0.3867	0.4549	0.4669	0.3490	0.3544	0.5654	0.4994
Pharmaceuticals & Biotechnology	0.1083	0.1497	0.3096	0.4941	0.5716	0.5511	0.8063	0.7763
Real Estate Investment & Services	0.2712	0.2669	0.3962	0.3875	0.3110	0.3143	0.2945	0.4995
Real Estate Investment Trusts	0.5644	0.4661	0.6374	0.5280	0.4517	0.3935	0.5088	0.5119
Software & Computer Services	0.2357	0.2754	0.3332	0.4179	0.3165	0.3542	0.5463	0.5366
Support Services	0.5868	0.6124	0.5531	0.6671	0.4886	0.5055	0.6747	0.5751
Technology Hardware & Equipment	0.2957	0.2976	0.7665	0.5724	0.7246	0.5709	0.7576	0.7465
Chemicals	0.2923	0.5092	0.7066	0.6060	0.5565	0.4820	0.4983	0.5862
Financial Services	0.6141	0.5383	0.4359	0.6139	0.4779	0.4747	0.5034	0.5691
Food Producers	0.3801	0.4031	0.4712	0.4667	0.2745	0.3432	0.6222	0.4826
General Industrials	0.4394	0.5661	0.3311	0.5649	0.4460	0.3829	0.5002	0.4677
General Retailers	0.6171	0.5025	0.6375	0.6090	0.4140	0.4909	0.3271	0.5974
Industrial Engineering	0.6618	0.5338	0.7279	0.7040	0.4140	0.6125	0.7717	0.7088
Life Insurance	0.6175	0.5898	0.6653	0.5854	0.4170	0.3981	0.4712	0.4750
Mobile Telecommunications	0.4841	0.4983	0.5729	0.5278	0.3954	0.3721	0.4069	0.4796
Travel & Leisure	0.3718	0.3926	0.6715	0.4803	0.3222	0.3705	0.4706	0.5135

Table 8.6…continued

Sector	Multiple							
	NClfIA		OD		FCFE		FCFF	
	Act	Pre	Act	Pre	Act	Pre	Act	Pre
Construction & Materials	1.0411	1.0481	0.3977	0.4060	0.7734	0.7578	0.6343	0.5397
Electronic & Electrical Equipment	0.6749	0.7088	0.4838	0.5100	0.6863	0.6545	0.6458	0.5532
Equity Investment Instruments	0.5675	0.5519	0.6335	0.6388	0.5545	0.5919	0.5532	0.5798
Food & Drug Retailers	0.7267	0.7290	0.6754	0.8250	0.6319	0.6014	0.8511	0.6333
Industrial Metals & Mining	0.5811	0.6551	0.5508	0.5453	0.7018	0.6347	0.6965	0.5601
Industrial Transportation	0.8195	0.8115	0.3594	0.3417	0.6576	0.7111	0.4408	0.5147
Mining	0.8657	0.9107	0.3390	0.3858	0.7303	0.7275	0.5962	0.5295
Pharmaceuticals & Biotechnology	1.5379	1.6682	0.4978	0.5908	0.8414	0.8774	0.4697	0.6094
Real Estate Investment & Services	1.1132	1.1130	0.3716	0.3005	0.9510	0.7934	0.7053	0.5156
Real Estate Investment Trusts	0.8691	0.7929	0.3279	0.4595	0.7325	0.6847	0.6428	0.5436
Software & Computer Services	1.0842	1.1464	0.4083	0.3567	0.8884	0.7913	0.6863	0.5310
Support Services	0.5675	0.6278	0.5341	0.6492	0.5056	0.6088	0.5642	0.5852
Technology Hardware & Equipment	1.5356	1.3801	0.7292	0.6561	0.7097	0.7939	0.6841	0.6151
Chemicals	0.8088	0.8162	0.5079	0.5905	0.7014	0.6663	0.5881	0.5775
Financial Services	0.7492	0.7449	0.6780	0.5882	0.7493	0.6491	0.6926	0.5743
Food Producers	0.9284	0.8613	0.3036	0.3749	0.3927	0.7173	0.2623	0.5249
General Industrials	0.4020	0.5672	0.5766	0.4711	0.8281	0.6266	0.5634	0.5381
General Retailers	0.9620	0.8418	0.6838	0.6009	0.6373	0.6707	0.2148	0.5811
Industrial Engineering	0.8921	0.9329	0.9904	0.7738	0.7289	0.6614	0.5507	0.6280
Life Insurance	0.6324	0.5366	0.5042	0.4978	0.4791	0.6141	0.4045	0.5437
Mobile Telecommunications	0.6773	0.6969	0.5537	0.4388	0.5933	0.6647	0.4917	0.5348
Travel & Leisure	1.0239	0.9190	0.3038	0.4092	0.7495	0.7252	0.4098	0.5357

Table 8.7: Predictivity readings of 16 multiples

Multiple	Predictivity
GP	0.2910
EBITDA	0.7170
EBIT	0.6870
PAT	0.6710
PBT	0.8470
HE	0.5190
TA	0.6540
IC	0.7520
BVE	0.5780
R	0.3390
CgbO	0.6410
NCIfOA	0.4620
NCIfIA	0.9230
OD	0.6880
FCFE	0.3170
FCFF	0.0570

8.6   CONCLUSION

The aim of Chapter 8 was to validate H5, i.e. to verify or reject the hypothesis that the valuation accuracy of multiples is industry-specific. The evidence suggests that the optimal choice of value driver depends on the sector in which the target entity resides and therefore also answers research question five, i.e. industry-specific multiples do improve the valuation accuracy of multiples.

However, prior to testing the industry-specific nature of the multiples, it was first necessary to establish which PGVs best suited which sectors. None of the peer group selection methods offered evidence to suggest that they were the optimal choice across all 28 sectors. Therefore, one can conclude that the optimal choice of PGV is also industry-specific.

The research results confirmed and contradicted the cross-sectional-based evidence obtained from Chapter 5. As was the case with Chapter 5, the evidence indicated that multiples based on single valuation fundamentals produced the least accurate valuations across all 28 sectors. However, while the results in Chapter 5 suggested that a combination of valuation fundamentals, RoE.Rg and RoE.TA in particular, offered superior explanatory power *vis-à-vis* industry classifications, the evidence from Chapter 8 suggested a different approach. Apart from multiples whose peer groups are based on single valuation fundamentals, which produced the least accurate valuations, none of the other seven PGVs offered particularly superior or inferior valuation performances. Therefore, the superior valuation performance of multiples whose peer groups are based on a combination of valuation fundamentals, RoE.Rg in particular, as deduced from the cross-sectional analysis conducted in Chapter 5, does not seem to hold on a per sector basis.

An SVC was subsequently created, which ranked each of the 16 multiples according to the valuation accuracy they exhibited in each of the 28 sectors. The SVC reflected substantial potential precision gains, ranging from 43.27% to 218.33%, and confirmed earlier findings in Chapter 7 regarding the valuation performance of the 16 value drivers. Earnings-based value drivers dominated the top positions in the SVC, producing the most accurate valuations over 75.00% of the sectors, confirming their superior explanatory power *vis-à-vis* asset, revenue-, dividend- and cash flow-based value drivers. Also in line with earlier findings in Chapter 7, HE was again confirmed as the most accurate individual driver, producing the most accurate valuations in 50.00% of the sectors.

The research results therefore presented empirical evidence in support of the use of industry-specific multiples. Equally evident was that peer group selection methods are industry-specific. Investment practitioners' use of industry-specific multiples in the South African market seems well justified. However, investment practitioners should perhaps also consider more carefully their choice of PGV, since this may secure precision gains of up to 83.18%.

The evidence obtained from Chapters 4 to 8 affords one the opportunity to construct optimal industry-specific single factor multiples models. These single factor multiples

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models will subsequently be compared to industry-specific composite multiples models in Chapter 9.

CHAPTER 9

THE VALUATION PERFORMANCE OF COMPOSITE MULTIPLES MODELS

9.1   INTRODUCTION

In Chapter 9 composite models are constructed for each of the six key industries in South Africa. The objective is to ascertain whether composite multiples models produce more accurate equity valuations than optimal equity-based single factor multiples models. The analysis will be conducted on an industry basis, since it is anticipated that different composite multiples models will suit different industries, as was the case with single factor multiples models in Chapter 8. An optimal equity-based composite multiples model will be constructed for each of the six industries and their valuation accuracy will be compared to that of the eight equity-based single factor multiples models, as contained in Table 9.1. The aim is to validate H6, which postulates:

H6:   Industry-specific composite multiples models offer higher degrees of valuation accuracy *vis-á-vis* industry-specific single factor multiples models.

Firstly, the weight allocations of the composite models' components are determined. This is achieved by employing optimisation applications with the goal of minimising the SAVE and the MVE. Secondly, the increase in valuation accuracy that composite multiples models may offer over single factor multiples models is estimated. Thirdly, the consistency of the results is assessed over the period 2001 to 2010.

Since various single factor multiples are typically included in investment practitioners' reports there seems to be a case for compiling a composite of these single factor multiples. However, composite modelling is, as of yet, largely an unexplored phenomenon in the South African market and the emerging market literature offers little guidance to investment practitioners in this regard. It is hoped that the findings from Chapter 9 will offer a new perspective for the composition of composite multiples models in emerging markets and in South Africa in particular.

9.2 LITERATURE REVIEW

Most of the existing international literature focuses on a composite of earnings (P/EPS) and book value (P/BVE). The use of a composite of P/EPS and P/BVE stems from the many researchers who have attempted to investigate the nature of the relationship between accounting data and entity value by focusing on these two multiples (Ohlson & Juettner-Nauroth, 2005; Penman, 1998; Ohlson, 1995). Cheng and McNamara (2000) compared the P/EPS, P/BVE and an equally weighted combination of P/EPS and P/BVE over a period of 20 years from 1973 to 1992 by extracting data from the Industrial Compustat database. Cheng and McNamara (2000) found that a combination of P/EPS and P/BVE outperforms the individual P/EPS and P/BVE multiples. In a similar study conducted in the USA and Europe, Schreiner (2007) tested the valuation accuracy of a two-factor composite model consisting of P/BVE and other earnings-based multiples. He found that a significant valuation performance improvement occurred when opting for a two-factor valuation model *vis-á-vis* a single-factor valuation model.

Chan (2009) also investigated a two-factor composite model, consisting of P/EPS and P/BVE, for USA-based entities over the period 1982 to 2004, but, contrary to previous studies, allowed the weighting for these multiples to vary. Besides the fact that Chan's findings concurred with previous research, they also suggested that a composite multiple with unrestricted weightings increased the valuation accuracy over an equally weighted composite multiple. In a similar study, Henschke and Homburg (2009) compared an equally weighted composite model of P/BVE, P/EPS and P/EPS (forecast), for entities in the USA over the period 1986 to 2004, and found that the composite models outperformed individual multiples.

Penman (1998) tested composite multiples for American entities based on EPS, book value and price data obtained from the Compustat database for the 25-year period 1968 to 1993. Penman based the weightings on the relative difference between earnings and book value, which varied over time. In keeping with Chan's (2009) results, Penman suggested that the weightings should be adjusted according

to the spread between earnings and book value over time, i.e. unrestricted weightings increase the valuation accuracy.

Extracting data from the Compustat and IBES databases for the period 1981 to 1999, Yoo (2006) tested the valuation accuracy of a composite of earnings, book value, EBITDA and revenue multiples compared to the respective individual multiples. The results indicated that the composite model offered an increase in valuation accuracy over the use of individual multiples.

While almost all of the studies mentioned above limited the number of composite variables to two, even the most comprehensive of these studies failed, amongst other limitations, to include cash flow value driver-based multiples in the composite multiple or to distinguish between equity- and entity-based multiples. Other limitations of previous research include the use of restricted weightings, limited or non-industry specific analysis and the absence of non-linear weight allocations. In this study, these limitations will be addressed by the empirical testing, by means of linear modelling and/or non-linear weight allocations, of the valuation accuracy of composite models that combine information from various value driver categories, including cash flows. The aim is to ascertain whether equity valuations based on unrestricted, industry-specific composite multiples outperform valuations based on industry-specific single factor multiples in terms of valuation accuracy.

All the evidence from the developed market literature, therefore, suggests that composite modelling produces more accurate valuations than single factor multiples modelling. What does the emerging market literature reveal? The only documented study on composite modelling in emerging markets was conducted by Sehgal and Pandey (2010), who tested the valuation performance of two-factor composite models in Brazil, India, China, South Korea and South Africa, over the period 1993 to 2007. They concluded, among other findings, that two-factor composite models produce neither significantly, nor consistently, more accurate valuations than single factor multiples models, which contradicts evidence from the developed market literature.

Unfortunately, the scope of the study by Sehgal and Pandey was limited. Aside from its limitations, as discussed in Section 7.2, their study did not accommodate a multi-factor composite modelling alternative, but instead limited their composite models to a combination of only two single factor multiples models. Regrettably, the limited scope of the study by Sehgal and Pandey prohibits a more detailed analysis. Consequently, the research conducted in Chapter 9 aims to broaden the scope of the South African case study, in particular, by including eight equity-based single factor multiples, based on value drivers representing all of the major equity-based value driver categories, namely earnings, assets, dividends and cash flows.

9.3   DATA SELECTION

From the initial analysis of the 16 multiples that are contained in Table 2.1, the focus in Chapter 9 shifts to equity-based multiples in particular. The equity-based comparison of the composite multiples models with single factor multiples models stems from the objective of this study, which is to investigate the valuation accuracy of equity-based composite multiples models in particular. To this end, the proper construction of single factor equity-based multiples models first had to be investigated in Chapters 4 to 8. The issue pertaining to the most accurate MPV basis was addressed in Chapter 6, indicating that MCap is the more accurate alternative, despite the theory and design of the study being biased in favour of MVIC.[43] Consequently, the composite models constitute equity-based compilations of the eight equity-based single factor multiples models, as contained in Table 9.1.

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[43]   Although one may be tempted to incorporate entity-based single factor multiples into the equity-based composite model, this will result in model inconsistencies, which, as alluded to in Section 2.4.1, may obscure the interpretation of the results. Therefore, although entity-based composite modelling is not the focus of this dissertation, it could prove to be an interesting future research project.

Table 9.1

Equity-based single factor multiples

		Value drivers			
		Earnings	**Assets**	**Dividends**	**Cash flow**
MPV	**P**	PBT	BVE	OD	NCIfOA
		PAT			NCIfIA
		HE			FCFE

Note that the matching principle is applied for the selection of the equity-based value drivers, i.e. the value drivers represent claims to equity holders in particular. Also note that only four value driver categories are presented in Table 9.1, since the revenue category contained only one value driver, which is entity-based. The number of observations varied for each equity-based multiple, depending on the specific industry in question and how well the multiples satisfied the criteria stipulated in Section 3.2. For the purpose of composite modelling in particular, the population sizes per industry varied between 242 and 1 248 observations.

9.4   RESEARCH METHODOLOGY

For the purpose of investigating the valuation accuracy of composite multiples models, Equation (3.7) from Section 3.4.2 is employed:

$$\hat{V}_{it}^e = \sum_{j=1}^{k} \beta_{jt} \cdot \hat{\lambda}_{jpt}^e \cdot \alpha_{jit} \qquad (3.7)$$

where $\hat{V}_{it}^e$ is the predicted equity value of entity i at time t and $\hat{\lambda}_{jpt}^e \cdot \alpha_{jit}$ represents each single-factor equity value prediction (j) that is included in the composite multiples. The optimal number of single factor multiples models that is catered for in each composite model will depend on the optimal weightings as obtained from the optimisation applications. It is envisaged that these multiples will be drawn from

various value driver categories, which may include earnings, assets, dividends and cash flows. Although a high level of multicollinearity is expected amongst the respective value drivers, careful statistical analysis by means of PCA can be employed to mitigate such an occurrence.

The assumptions regarding β are that

$$0 \leq \beta_{1t}, \ \beta_{2t}, ..., \beta_{kt} \leq 1$$

and

$$\sum_{j=1}^{k} \beta_{jt} = 1$$

The composite multiple's predicted equity value will therefore encapsulate the weighted average of the predicted values of the respective single factor multiples. It was initially envisaged that regression analysis, specifically PCR, which is ideally suited to highly correlated predictor variables, would be used to derive the optimal weights for each of the single factor multiples.

However, upon analysing the diagnostic characteristics of the residuals obtained from the PCR, it was evident that various assumptions of the standard Gauss-Markov theorem were violated. It is envisaged that non-linear regression modelling by way of ridge regression or PCR could be workable alternatives, but this will require data imputations, and thus falls outside the scope of this study.

The initial analysis focuses on the correlation matrices of all 16 value drivers as contained in Table 2.1. The analysis is subsequently narrowed down to the equity-based value drivers in particular. This is followed by the compilation of composite multiples models for each of the six key industries in South Africa. The valuation performance of these composite models is then compared to that of the single factor multiples models, as contained in Table 9.1, to determine the magnitude of the

increase in valuation accuracy, if any. Lastly, the consistency of the results is investigated over the ten-year period between 2001 and 2010.

9.5 EMPIRICAL RESULTS

In Chapters 4 to 7, the 16 multiples contained in Table 2.1 were subjected to a comprehensive cross-sectional analysis in order to gauge their valuation performance in various scenarios. This was followed by an industry analysis in Chapter 8, which offered insight into the industry-specific nature of the multiples. The industry analysis afforded one the opportunity to observe behavioural differences in these multiples on an industry basis compared to their behaviour in the market as a whole.

Based on the results of the behavioural analysis of the preceding chapters, it is now possible to compile composite multiples models. The focus is primarily on equity-based multiples and their behaviour in each of six industries, namely Basic Materials, Consumer Goods, Consumer Services, Financials, Industrials and Technology.[44] It is anticipated that the composite multiples models may carry incremental information content *vis-á-vis* single factor multiples models and that this will culminate in an increase in valuation accuracy.

9.5.1 Consistency of the MPV and value drivers over time

An analysis of the observed relationships between MCaps over the period 2001 to 2010 is contained in Table 9.2. All the MCaps were positively correlated and very strongly so, with correlation coefficients ranging between 0.8472 and 0.9813. Therefore, a high market capitalisation in any particular year over the period 2001 to

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[44] As a result of data limitations, a sector-based approach, as adopted with the single factor multiples in Chapter 8, was not possible. Instead, an industry-based approach is adopted in Chapter 9. Although a total of 10 industries are demarcated on the McGregor BFA database, insufficient data is available for four of these industries, namely Health Care, Oil and Gas, Telecommunications and Utilities. Consequently, these four industries are omitted from the analysis in Chapter 9 and the focus is on the six key industries, for which sufficient data is available.

2010 is likely to be accompanied by a high market capitalisation in the other nine years as well.

A similar conclusion can be drawn from the value drivers that were analysed in Chapter 7. As is evident from the selection of value drivers in Table 9.2, all the observed relationships were positive and, with the exception of OD, NCIfIA and FCFE, these relationships were very strong, with correlation coefficients ranging between 0.7187 and 0.9896. Even among the three value drivers mentioned above, only a few pairwise combinations of years exhibit a relatively poor correlation coefficient compared to the other value drivers.

The OD-based correlation coefficients are all positively and highly correlated, with the exception of the pairwise combination of years 2009 and 2001, where it is 0.6861, which, aside from being the only reading below 0.70, is still relatively high. Similarly, the FCFE-based correlation coefficients are all positively and highly correlated, with the exception of the pairwise combination of years 2008 and 2003, where it is 0.6734, which, aside from being the only reading below 0.70, is still relatively high. The NCIfIA-based correlation matrix, however, contains five correlation coefficients below 0.70. They are the pairwise combination of 2001 with 2009 and 2010, and the pairwise combination of 2004 with 2007, 2008 and 2009.

Therefore, barring these few exceptions, one can deduce that a high estimate of market capitalisation based on these value drivers in any particular year over the period 2001 to 2010 is likely to have produced a high estimate of market capitalisation in the other nine years as well. However, given the selection of value drivers, the existence of a high degree of multicollinearity is also likely.

Table 9.2: Correlation matrices of MCap and a selection of value drivers over the period 2001 to 2010

MCap

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9758	1.0000								
2008	0.9535	0.9759	1.0000							
2007	0.9384	0.9548	0.9660	1.0000						
2006	0.9223	0.9304	0.9299	0.9572	1.0000					
2005	0.9213	0.9200	0.9238	0.9344	0.9769	1.0000				
2004	0.9055	0.9086	0.9109	0.9150	0.9533	0.9813	1.0000			
2003	0.8713	0.8782	0.8901	0.8935	0.9215	0.9515	0.9678	1.0000		
2002	0.8616	0.8677	0.8750	0.8803	0.9103	0.9380	0.9488	0.9787	1.0000	
2001	0.8472	0.8550	0.8660	0.8707	0.8951	0.9191	0.9247	0.9521	0.9707	1.0000

HE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9192	1.0000								
2008	0.9150	0.9211	1.0000							
2007	0.9127	0.9056	0.9418	1.0000						
2006	0.8791	0.8631	0.9142	0.9454	1.0000					
2005	0.8742	0.8670	0.8927	0.9192	0.9549	1.0000				
2004	0.8683	0.8390	0.8791	0.8980	0.9265	0.9574	1.0000			
2003	0.8345	0.8521	0.8417	0.8941	0.9200	0.9265	0.9532	1.0000		
2002	0.8327	0.7971	0.8315	0.8718	0.9037	0.8848	0.9153	0.9525	1.0000	
2001	0.8238	0.8061	0.8156	0.8346	0.8646	0.8482	0.8773	0.9173	0.9313	1.0000

Table 9.2…continued

BVE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9543	1.0000								
2008	0.9478	0.9654	1.0000							
2007	0.9240	0.9233	0.9327	1.0000						
2006	0.9123	0.9192	0.8969	0.9553	1.0000					
2005	0.9024	0.9045	0.9022	0.9376	0.9675	1.0000				
2004	0.8857	0.8776	0.8794	0.9046	0.9511	0.9638	1.0000			
2003	0.8665	0.8639	0.8473	0.8915	0.9115	0.9317	0.9504	1.0000		
2002	0.8521	0.8564	0.8388	0.8796	0.8982	0.9079	0.9150	0.9699	1.0000	
2001	0.8485	0.8538	0.8318	0.8771	0.8858	0.8931	0.9018	0.9452	0.9687	1.0000

OD

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9165	1.0000								
2008	0.8753	0.8752	1.0000							
2007	0.8620	0.8760	0.9461	1.0000						
2006	0.8304	0.7708	0.8652	0.9240	1.0000					
2005	0.7834	0.7326	0.8406	0.8918	0.9390	1.0000				
2004	0.7751	0.7481	0.8318	0.8768	0.8891	0.9023	1.0000			
2003	0.7742	0.7495	0.8036	0.8468	0.8704	0.8688	0.8899	1.0000		
2002	0.7174	0.7117	0.7749	0.8290	0.8559	0.8602	0.8723	0.9060	1.0000	
2001	0.7378	0.6861	0.7610	0.7913	0.8284	0.8165	0.8580	0.8329	0.8233	1.0000

Table 9.2…continued

FCFE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.8215	1.0000								
2008	0.7817	0.7725	1.0000							
2007	0.7573	0.8436	0.8204	1.0000						
2006	0.7879	0.8268	0.6953	0.8163	1.0000					
2005	0.8474	0.8139	0.7404	0.7579	0.8294	1.0000				
2004	0.8227	0.7537	0.7494	0.7695	0.8065	0.8282	1.0000			
2003	0.8173	0.8165	0.6734	0.7757	0.8302	0.8389	0.8477	1.0000		
2002	0.7254	0.7272	0.7103	0.7657	0.7771	0.7664	0.7902	0.8472	1.0000	
2001	0.7582	0.7021	0.7191	0.7156	0.8494	0.8034	0.7876	0.7996	0.7690	1.0000

Note that the correlation matrices contain the logged correlation coefficients. There were numerous outliers in this study, which decreased the correlation coefficients. Consequently, a logged analysis was deemed more appropriate since it diminished the impact of these outliers. A complete list of the correlation matrices of all 16 value drivers is contained in Annexure E.

Table 9.3: Correlation matrix between the 16 value drivers for 2010

	GP	EBITDA	EBIT	PBT	PAT	HE	TA	BVE	IC	T	CgbO	NCIfOA	NCIfIA	OD	FCFF	FCFE
GP	1.0000															
EBITDA	0.9153	1.0000														
EBIT	0.9102	0.9892	1.0000													
PBT	0.8670	0.9379	0.9466	1.0000												
PAT	0.8687	0.9419	0.9548	0.9912	1.0000											
HE	0.8502	0.9144	0.9247	0.9404	0.9380	1.0000										
TA	0.8643	0.9174	0.9275	0.8442	0.8598	0.8635	1.0000									
BVE	0.7709	0.8534	0.8582	0.8007	0.8292	0.8173	0.9307	1.0000								
IC	0.8539	0.9070	0.9175	0.8313	0.8488	0.8531	0.9942	0.9242	1.0000							
T	0.9485	0.8908	0.8807	0.8586	0.8471	0.8207	0.8332	0.7389	0.8217	1.0000						
CgbO	0.9248	0.9479	0.9441	0.8941	0.8965	0.8853	0.9015	0.8247	0.8881	0.9023	1.0000					
NCIfOA	0.8733	0.9047	0.8885	0.8734	0.8669	0.8467	0.8609	0.8021	0.8433	0.8858	0.9431	1.0000				
NCIfIA	0.7892	0.8224	0.8157	0.7987	0.7876	0.7525	0.8020	0.7641	0.7858	0.7617	0.8646	0.8802	1.0000			
OD	0.7400	0.7798	0.7903	0.8180	0.8237	0.7952	0.7425	0.7330	0.7347	0.6934	0.7460	0.6919	0.6220	1.0000		
FCFF	0.8967	0.9026	0.9071	0.8735	0.8655	0.8674	0.8934	0.8145	0.8789	0.8734	0.9602	0.9202	0.8828	0.7161	1.0000	
FCFE	0.8313	0.8821	0.8901	0.8567	0.8469	0.8275	0.8683	0.7924	0.8523	0.8077	0.8986	0.8928	0.9102	0.7311	0.9209	1.0000

9.5.2   Multicollinearity

Table 9.3 contains the pairwise Pearson correlations of all 16 value drivers for 2010. All 16 value drivers exhibit positive and very strong relationships. Overall, the correlation coefficients range between 0.6220 and 0.9942, which may suggest that not all the value drivers share the same information content.

Two exceptions are noted, namely the pairwise combinations OD and NCIFOA and OD and NCIfIA. These two, cash flow-based, combinations are the only value drivers that exhibit correlation coefficients of less than 0.70. This might suggest that OD, NCIfOA and NCIfIA carry incremental information content, not only relative to the other cash flow-based value drivers, but across all the value drivers, i.e. also those that were extracted from other types of financial statements.

From the analyses conducted in Chapter 7 and Chapter 8, it is evident that the construction of a composite multiples model should incorporate HE as an independent variable. From the correlation coefficient matrix in Table 9.3, it seems prudent to consider OD or NCIfIA as a second independent variable. However, a *carte blanche* application of such a composite model is not warranted. Each of the six industries should be considered in isolation and a composite model consisting of a combination of HE, OD and NCIfIA may not be the *de facto* best choice for inclusion in every composite model.

From a financial statement perspective, all value drivers that were extracted from the same type of financial statement have high correlation coefficients, i.e. they share considerable information content. Value drivers that were extracted from the statement of financial position, in particular, exhibit very high correlation coefficients, in the vicinity of 0.90 or more. Similarly, value drivers that were extracted from the statement of comprehensive income and the cash flow statement share considerable information content, which is evident from their respective correlation coefficients of around 0.85 or more. This suggests a high likelihood of encountering a fair amount of multicollinearity when employing normal regression analysis to the data.

The correlation matrices discussed thus far were based on the market as a whole and on all 16 value drivers. However, the focus of the construction of the composite multiples models is on equity-based models in particular. Consequently, it is equally important to compare the correlation coefficients of the equity-based value drivers on an industry basis, since this forms the basis of the composite modelling. Table 9.4 contains these matrices for 2010.

The correlation coefficients contained in Table 9.4 indicate that the Basic Materials and Financials industries also exhibit positive and very high correlations among the equity-based value drivers, on which the composite modelling is based. Although the majority of the pairwise correlations in the Consumer Goods industry are highly positive, NCIfIA and OD exhibit a pairwise correlation of 0.5467, which is poor. In the Consumer Services industry, NCIfIA is poorly correlated with all the earnings-based value drivers, indicating pairwise correlation coefficients of between 0.5216 and 0.5875. NCIfIA is particularly poorly correlated with OD, which is indicated by a correlation coefficient of 0.2182. In the Industrials industry, NCIfIA is poorly correlated with all the non-cash-flow-based value drivers, which is reflected in correlation coefficients of between 0.3653 and 0.6277, while OD is poorly correlated with BVE (0.6301) and all the cash flow-based value drivers, which is reflected by correlation coefficients of between 0.3653 and 0.6453. In the Technology industry it is evident that OD is poorly correlated with all the other value drivers, reflecting correlation coefficients of around 0.40, or less, while NCIfIA is poorly correlated with BVE, indicating a correlation coefficient of 0.5303.

Table 9.4: Correlation matrices for each of the six key industries for 2010

Basic Materials								
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9934	1.0000						
HE	0.9150	0.9178	1.0000					
BVE	0.7833	0.8217	0.7915	1.0000				
OD	0.7478	0.8432	0.8503	0.8185	1.0000			
NCIfOA	0.9128	0.9083	0.8888	0.9111	0.8658	1.0000		
NCIfIA	0.8407	0.7946	0.7405	0.8611	0.7410	0.9068	1.0000	
FCFE	0.8408	0.8081	0.7223	0.7598	0.7542	0.8730	0.9428	1.0000

Consumer Goods							
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9968	1.0000						
HE	0.9874	0.9888	1.0000					
BVE	0.9189	0.9192	0.9125	1.0000				
OD	0.7402	0.7274	0.7346	0.6971	1.0000			
NCIfOA	0.9521	0.9562	0.9592	0.9247	0.6855	1.0000		
NCIfIA	0.7640	0.7694	0.7771	0.7242	0.5467	0.8454	1.0000	
FCFE	0.8951	0.8981	0.9114	0.8915	0.7738	0.9287	0.8011	1.0000

Consumer Services							
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9989	1.0000						
HE	0.9156	0.9506	1.0000					
BVE	0.7991	0.8674	0.8391	1.0000				
OD	0.8372	0.8327	0.7884	0.7326	1.0000			
NCIfOA	0.8119	0.8743	0.8096	0.8114	0.6325	1.0000		
NCIfIA	0.5875	0.5216	0.5571	0.7103	0.2182	0.7344	1.0000	
FCFE	0.7888	0.8136	0.7594	0.7140	0.5787	0.9196	0.8102	1.0000

Financials							
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9965	1.0000						
HE	0.9310	0.9255	1.0000					
BVE	0.7886	0.8456	0.8060	1.0000				
OD	0.9198	0.9179	0.8411	0.7646	1.0000			
NCIfOA	0.8222	0.8069	0.7653	0.7282	0.7029	1.0000		
NCIfIA	0.8359	0.8147	0.7795	0.8216	0.7875	0.8855	1.0000	
FCFE	0.8596	0.8461	0.8144	0.7921	0.8850	0.8713	0.9541	1.0000

Table 9.4…continued

Industrials							
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9744	1.0000						
HE	0.9768	0.9478	1.0000					
BVE	0.7956	0.7493	0.8120	1.0000				
OD	0.8452	0.8336	0.8530	0.6301	1.0000			
NCIfOA	0.7927	0.7550	0.8039	0.7868	0.6319	1.0000		
NCIfIA	0.6277	0.5840	0.5811	0.5375	0.3653	0.8136	1.0000	
FCFE	0.7877	0.7500	0.7941	0.7049	0.6453	0.8970	0.8640	1.0000

Technology								
	PBT	**PAT**	**HE**	**BVE**	**OD**	**NCIfOA**	**NCIfIA**	**FCFE**
PBT	1.0000							
PAT	0.9925	1.0000						
HE	0.9627	0.9644	1.0000					
BVE	0.8476	0.8567	0.8080	1.0000				
OD	0.3498	0.3944	0.4284	0.3228	1.0000			
NCIfOA	0.8242	0.8371	0.8109	0.7965	0.2337	1.0000		
NCIfIA	0.6581	0.6804	0.7286	0.5303	-0.0097	0.9629	1.0000	
FCFE	0.8001	0.8165	0.8321	0.7861	0.3799	0.9332	0.9789	1.0000

9.5.3   Regression analysis

The data was subjected to a PCA on a per industry basis, after which PCR analysis was applied to the resulting two or three principal components. Although the composite modelling via PCR indicated R-squared values of between 0.75 and 0.95, with statistically significant coefficients, at least at the 95% confidence level, and of the correct sign (positive), various assumptions of the standard Gauss-Markov theorem were violated. Consequently, the regression results were omitted from the analysis. Instead the composition of the composite models was based on alternative mathematical optimisation methods.

9.5.4   Optimisation procedures

Initial research conducted on the construction of composite multiples models focused on equally weighted models, which required no optimisation procedure. However, subsequent studies found that when these weights were not restricted, i.e. when the single factor multiples models were not allocated an equal weighting, the valuation accuracy of the composite multiples models increased *vis-á-vis* equally-weighted composite multiples models.

The objective of the resultant optimisation process in composite-based modelling was the minimisation of the valuation error as per Equation (3.4). A key focus point in the international literature in this regard is the minimisation of the median valuation error (Schreiner, 2007). Consequently, an *R function*, namely *MinMed3,*

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which focuses on the minimisation of the MVE, was written to implement the following:

Let $d_i = \left(\dfrac{|y_i - \mathbf{m}'_i \mathbf{a}|}{y_i} \right)$ $\qquad\qquad for\ i = 1,\ 2, \ldots, n$ $\qquad\qquad\qquad$ (9.1)

subject to the constraints $\begin{cases} \displaystyle\sum_{i=1}^{p} a_i = 1 \\ a_i \geq 0\ for\ all\ i. \end{cases}$

The median of Equation (9.1) is minimised by *MinMed3*. In Equation (9.1) y_i is the ith actual equity value, while $\mathbf{m}'_i$ represents a vector of equity value estimates corresponding to y_i and $\mathbf{a}$ denotes the weight allocation to each single factor multiple. The output of *MinMed3* contained the optimal weights of the various single factor multiples models contained in the composite multiples models.

Since the objective of the optimisation process is to determine the optimal weights that should be allocated to the single factor multiples models contained in each composite model, the problem is essentially one of mathematical optimisation. However, given the nature of the minimisation objective of the optimisation function, there is no closed form algebraic solution to the optimisation objective. Consequently, it was deemed prudent to employ two additional optimisation methods, namely SSVE and SAVE.[45] Two restrictions were imposed on all three methods. The first was that the weightings had to add up to one and the second was that all the weightings had to be positive.

The MVE approach, which was adopted to enable comparison with findings from the developed market literature, was effected via the *solnp* function, a non-linear optimisation function based on the Lagrange method, in the *R-package Rsolnp*. As

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[45] The SSVE method was applied via the *solve.QP* function in the *R-package Quadprog*, with similar results. However, given the non-linear nature of the data and its other limitations, as discussed in Chapter 3, these results are not shown here.

with any mathematical optimisation method, the *solnp* function in the *R-package Rsolnp* requires the specification of starting parameter vectors. The solution offered by *solnp*, or any other optimisation function, is dependent on these starting parameter vectors. When the starting parameter vectors are omitted, the *solnp* function assumes equally weighted starting parameter vectors by default. However, omitting the starting parameter vectors may potentially increase the risk of encountering local minimums, which may not be optimal, i.e. they could differ substantially from global minimums (Nel, Bruwer & Le Roux*,* 2014d).

One method of addressing the risk of local minimums *vis-á-vis* global minimums is by altering the starting parameter vectors, i.e. by using various different (random) starting parameter vectors, and by repeating the optimisation process. The most optimal solution set would be the one that produces the lowest valuation error, which, if repeated often enough, should be very close to the global minimum, or at least immaterially different from it. Intuitively then, one could use the optimal output of a previous run of the same method or the optimal output of a different optimisation method as starting parameter vectors. The latter approach was adopted in this study. The optimised output, i.e. the weight allocations in the composite models that produced the most accurate valuations, from the SAVE method, was used as the set of starting parameter vectors for the MVE method. The *lp* function, which is a linear and integer programming application in the *R-package lpSolve,* was used to apply the SAVE method, while the *solnp* function in the *R-package Rsolnp* was used to apply the MVE method*.* The objective with the *lp* function was to produce optimal weights to be allocated to each of the single factor multiples models included in the composite multiples models, in order to minimise the SAVE. To this end, the *R function SAVE* was written to effect the optimisation of the objective function (9.2).

$$\min_{\mathbf{a}} \sum_{i=1}^{u} \left(\frac{\left| y_i - \mathbf{m}_i' \mathbf{a} \right|}{y_i} \right) \tag{9.2}$$

subject to $\quad \begin{cases} \displaystyle\sum_{i=1}^{p} a_i = 1 \\ a_i \geq 0 \ \textit{for all i.} \end{cases}$

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The output of *SAVE,* i.e. the optimal weights of the various single factor multiples based on the SAVE method, were used as the set of starting parameter vectors in the *MinMed3* function. Table 9.5, for example, illustrates the results of the optimisation process for 2010. Note that all the single factor multiples originally start with an equal weighting of 0.125 in *SAVE*, after which the output of *SAVE* becomes the starting parameter vectors in *MinMed3*. As is evident from Table 9.5, the output from *SAVE* is optimised further via *MinMed3* to eventually reach the optimal MVE-based weights. A substantial improvement in the valuation accuracy of the new composite-based model *vis-á-vis* the original run/method would imply that one has moved substantially closer to the global minimum (Nel, Bruwer & Le Roux*,* 2014d). Although it is impossible to know whether the final solution constitutes the global minimum, one has to bear in mind that the verification of H6 does not require the valuation error to be the global minimum. H6 merely posits that composite multiples models produce more accurate valuations *vis-á-vis* single factor multiples models and, as the results in the next section will indicate, the latter was confirmed without the knowledge of the actual global minimum valuation errors.

9.5.5   Composition of the composite models

In order to compile the composite multiples models, it was necessary to obtain the optimal weights for each of the components to be included in each model. All eight equity-based single factor multiples contained in Table 9.1, namely P/PBT, P/PAT, P/HE, P/BVE, P/OD, P/NCIfOA, P/NCIfIA and P/FCFE, were considered for inclusion in the composite models. These eight single factor multiples emanate from four different value driver categories, namely earnings, assets, dividends and cash flow. The inclusion of value drivers from four different value driver categories ensures that each value driver category potentially carries incremental information content, since all four value driver categories originate from different financial statements. PAT, for example, was extracted from the statement of comprehensive income and, while it is an indication of an entity's profitability, it does not represent cash in the bank for shareholders, i.e. PAT is unlikely to culminate in an equally valued cash dividend. In this case, OD would be a more realistic value driver from an equity holder's perspective.

Table 9.5: The optimisation process to determine the optimal weightings of the single factor multiples models, as included in the composite multiples models of six key South African industries for 2010

	Composites 2010							
	Value drivers							
	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Basic Materials								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	0.0131	-	0.4213	0.1617	-	0.4039	-	-
Optimal MVE-based weights	0.0026	-	0.4771	-	0.5203	-	-	-
Consumer goods								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	-	-	0.7674	0.0644	-	0.1683	-	-
Optimal MVE-based weights	-	-	0.8181	0.0929	0.0890	-	-	-
Consumer services								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	-	-	1.0000	-	-	-	-	-
Optimal MVE-based weights	-	-	1.0000	-	-	-	-	-
Financials								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	-	0.1593	0.8407	-	-	-	-	-
Optimal MVE-based weights	-	0.0206	0.9794	-	-	-	-	-
Industrials								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	-	-	0.2025	0.5047	0.0678	-	0.1991	0.0260
Optimal MVE-based weights	-	-	0.0057	0.6361	-	0.2679	0.0108	0.0795
Technology								
Initial SAVE-based weights	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weights	-	-	0.6583	-	-	0.3417	-	-
Optimal MVE-based weights	-	-	0.9675	-	0.0325	-	-	-

From these eight single factor multiples models, composite multiples models were constructed for each of the six key industries in the South African market. The breakdown of the composite models, based on the SAVE optimisation process, is contained in Table 9.6.

The following can be gleaned from the composite models: Firstly, composite models do not perform the most accurate equity valuations across the board. The evidence suggests that, in the Consumer Services industry, a single factor multiple, specifically P/HE, is the optimal choice of multiple in 2008 and 2010. Similarly, P/HE is the optimal choice of multiple in the Technology industry in 2003.

Secondly, the evidence suggests that there is no one-size-fits-all composite composition across all six industries, or even consistently so within any single industry. For example, while the composite multiples model in the Basic Materials industry in 2009 consists of five different single factor multiples models, the composite multiples model in 2001 consists of two.

Thirdly, note that, with the exception of 2007 in the Basic Materials industry, which consists of six single factor multiples models, none of the composite multiples models consists of more than five single factor multiples models, despite the availability of eight single factor multiples models. The composite multiples models predominantly consist of two to four single factor multiples models and the most common number of single factor multiples models included in the composite multiples models is three. This suggests that an *ad hoc* addition of single factor multiples models will not necessarily increase the valuation accuracy of the composite models.

Fourthly, note how earnings-based single factor multiples models dominate the composition of the composite multiples models over all six industries. On average, earnings-based value drivers, as a category, comprise between 40.90% and 89.68% of the composite models, which confirms the cross-sectional results obtained in

Table 9.6: Single factor multiples models and their weightings, as included in the composite multiples models of six key South African industries over the period 2001 to 2010

Basic Materials								
Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
2001	0.1264	-	-	0.8736	-	-	-	-
2002	-	-	0.6968	-	0.1792	0.1239	-	-
2003	-	-	0.4467	0.2870	-	0.2663	-	-
2004	-	-	0.3591	0.3359	0.3050	-	-	-
2005	0.1674	-	0.4562	-	-	0.0839	0.2924	-
2006	-	-	0.0277	0.1488	0.5697	0.0438	-	0.2099
2007	0.2886	-	0.1301	0.1951	0.0627	0.1276	0.1960	-
2008	-	0.5006	0.2826	0.2169	-	-	-	-
2009	0.1130	0.0605	-	0.3648	-	0.2906	0.1712	-
2010	0.0131	-	0.4213	0.1617	-	0.4039	-	-
Average	0.0708	0.0561	0.2820	0.2584	0.1117	0.1340	0.0660	0.0210
			0.4090	0.2584	0.1117			0.2210

Consumer Goods								
Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
2001	0.8311	0.1689	-	-	-	-	-	-
2002	-	0.4223	-	0.5402	0.0375	-	-	-
2003	-	0.5858	-	-	0.4142	-	-	-
2004	-	-	-	-	-	-	-	-
2005	-	-	0.2360	0.3720	-	-	-	0.3920
2006	0.0019	0.4197	-	0.3777	0.2006	-	-	-
2007	0.3086	-	0.5086	-	0.1828	-	-	-
2008	-	-	-	-	-	-	-	-
2009	-	-	0.6714	-	0.3286	-	-	-
2010	-	-	0.7674	0.0644	-	0.1683	-	-
Average	0.1427	0.1996	0.2729	0.1693	0.1455	0.0210	-	0.0490
			0.6152	0.1693	0.1455			0.0700

Table 9.6…continued

Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Consumer Services								
2001	-	0.6446	0.3554	-	-	-	-	-
2002	-	0.4408	0.0867	-	-	-	-	0.4724
2003	-	-	0.8185	-	0.1815	-	-	-
2004	-	-	0.9668	0.0322	-	0.0010	-	-
2005	-	-	0.8297	-	0.1002	-	0.0701	-
2006	-	-	0.9796	0.0204	-	-	-	-
2007	-	-	0.8814	-	0.0831	-	0.0354	-
2008	-	-	1.0000	-	-	-	-	-
2009	-	0.0269	0.9370	0.0310	-	-	0.0051	-
2010	-	-	1.0000	-	-	-	-	-
Average	-	0.1112	0.7855	0.0084	0.0365	0.0001	0.0111	0.0472
			0.8968	0.0084	0.0365			0.0584

Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Financials								
2001	-	-	0.7091	0.2909	-	-	-	-
2002	-	-	-	-	-	-	-	-
2003	-	-	-	0.2209	0.3656	-	0.4135	-
2004	0.0635	-	0.2384	-	0.1085	-	0.5895	-
2005	0.6187	-	0.1806	-	0.0946	-	0.0434	0.0627
2006	-	-	-	-	-	-	-	-
2007	-	-	-	0.8508	-	-	0.1492	-
2008	-	-	0.3766	-	0.6234	-	-	-
2009	-	-	0.7601	0.2399	-	-	-	-
2010	-	0.1593	0.8407	-	-	-	-	-
Average	0.0853	0.0199	0.3882	0.2003	0.1490	-	0.1495	0.0078
			0.4934	0.2003	0.1490			0.1573

Table 9.6…continued

Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Industrials								
2001	-	-	0.6565	0.1911	0.1317	-	-	0.0206
2002	-	0.0743	0.9212	-	0.0045	-	-	-
2003	-	0.0004	0.7157	-	0.1908	0.0931	-	-
2004	-	0.0117	0.8889	0.0994	-	-	-	-
2005	-	-	0.7668	-	0.2332	-	-	-
2006	0.1992	-	0.7950	-	0.0058	-	-	-
2007	-	-	0.2594	-	0.4280	0.3088	0.0038	-
2008	-	-	0.0085	0.3427	-	-	0.6488	-
2009	-	-	0.4477	0.0341	0.4261	0.0921	-	-
2010	-	-	0.2025	0.5047	0.0678	-	0.1991	0.0260
Average	0.0199	0.0087	0.5662	0.1172	0.1488	0.0494	0.0852	0.0047
			0.5948	0.1172	0.1488			0.1392

Years	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Technology								
2001	-	-	-	-	-	-	-	-
2002	-	-	-	-	-	-	-	-
2003	-	-	1.0000	-	-	-	-	-
2004	-	-	0.8605	0.1183	-	-	-	0.0212
2005	-	-	-	-	-	-	-	-
2006	0.1183	0.2650	0.4210	0.0258	0.1699	-	-	-
2007	-	-	0.8293	0.0696	-	0.1011	-	-
2008	-	-	0.6169	-	-	0.0970	0.0952	0.1909
2009	0.6933	-	0.0010	-	-	0.3057	-	-
2010	-	-	0.6583	-	-	0.3417	-	-
Average	0.1159	0.0379	0.6267	0.0305	0.0243	0.1208	0.0136	0.0303
			0.7805	0.0305	0.0243			0.1647

Note that there are years in which no weights are allocated to any of the single factor multiples, for example, 2004 in the Consumer Goods industry. This stems from insufficient data availability.

Chapter 7 and the industry-specific findings from Chapter 8. Earnings-based multiples carried a particularly heavy weighting in the Consumer Services and Technology industries, comprising, on average, 89.68% and 78.05% of the composite models, respectively.

On an individual value driver basis, on average, between 27.29% and 78.55% of the composite models contain HE, again confirming its superiority among the individual value drivers selected for this study. HE comprised, on average, more than half the composition of the composite models in three industries, namely Consumer Services (78.55%), Technology (62.67%) and Industrials (56.62%). PBT, which was ranked under the three most accurate multiples in 43% of the sectors analysed in the SVC in Table 8.5, managed to secure weightings of, on average, between 1.99% and 14.27% over all the industries, with the exception of the Consumer Services industry, where it failed to secure a weighting. Similarly, PAT carried an average weight of between 0.87% and 19.96% over all six industries. This concurs with its performance ranking obtained in the SVC in Chapter 8, where PAT was ranked as one of the three most accurate multiples in more than a third of the sectors analysed.

Fifthly, note the cash flow-based value driver category's unexpected contribution to the composition of the composite models. The evidence from Chapter 7 suggests that, as a value driver category, cash flows produced the least accurate valuations, even less so than revenue. However, on an individual value driver basis, two of the cash flow-based value drivers, namely NCIfOA and NCIfIA, occupied, on average, between 0.01% and 13.40% and between 1.11% and 14.95% component shares, respectively, over five of the six industries. NCIfOA failed to occupy a weighting in the Financials industry and NCIfIA failed to occupy a weighting in the Consumer Goods industry. NCIfIA in particular, when combined in a composite model with value drivers from other value driver categories, seems to contribute to a greater extent, in comparison with its isolation as a single factor multiple. This suggests that NCIfIA carries incremental information content, in addition to that offered by HE, for example. FCFE, the third cash flow-based value driver, had the lowest component share of all eight value drivers, occupying, on average, less than 5% of the composite models across all six industries. The latter concurs with the valuation

performance of FCFE, which was generally poor throughout the entire empirical study, continually producing among the least accurate valuations.

Sixthly, the asset-based value driver category, on average, occupied similar weightings to the cash flow-based value driver category. Although these two value driver categories, on average, on a per industry basis, managed to outperform each other interchangeably, their average weightings over all six industries were very similar. The contribution of BVE to the composite models varied between an average of 0.84% and 25.84% and was particularly prevalent in the Basic Materials and Financials industries, where it occupied, on average, 25.84% and 20.03% component shares, respectively. However, the contribution of BVE in the Consumer Services (0.84%) and Technology (3.05%) industries were insubstantial. It is of interest to note that, on average, BVE occupied a marginally smaller component share than the cash flow-based value driver category over all six industries. This is in stark contrast with findings in developed markets, where BVE is frequently included as a second most well-weighted constituent in composite modelling (Schreiner, 2007; Yoo, 2006; Penman, 1998).

Seventhly, the dividend-based value driver category, which, on average, over all six industries, occupied the smallest component share of all four value driver categories, contributed slightly less in a composite structure than when isolated as a single factor multiple, culminating in component shares of between an average of 2.43% and 14.90%. OD's weightings in the Consumer Services (3.65%) and Technology (2.43%) industries were insubstantial. OD carried its highest weighting in the Financials (14.90%), Industrials (14.88%) and Consumer Goods (14.55%) industries.

These results suggest that composite multiples models offer superior explanatory power compared to single factor multiples models. However, it is equally important to measure the increase in valuation accuracy that the composite multiples models may offer *vis-á-vis* the single factor multiples models. The applicability of composite multiples models will also depend on the consistency of their outperformance of the single factor multiples models over time.

9.5.6   Valuation accuracy and consistency over time

The relative valuation performances of the composite multiples models and single factor multiples models over the entire period from 2001 to 2010 are displayed in Table 9.7. The evidence suggests that composite multiples models carry incremental information content *vis-á-vis* single factor multiples models. The impact of the incremental information, as encapsulated in the composite models, on the valuation accuracy of equity-based multiples was measured over the period 2001 to 2010 and is also summarised in Table 9.7.

Note that the percentages in the IMP column in Table 9.7 indicate the extent to which equity-based composite multiples models outperformed the optimal equity-based single factor multiples models (highlighted) in each of the six industries. The description NA refers to industry years where there was insufficient data for comparison. A zero value in the IMP column, as is the case in the Consumer Services industry in 2008, for example, refers to industry years where specific single factor multiples models produced the most accurate multiple, i.e. where composite multiples models failed to produce more accurate valuations than single factor multiples models.

As is evident in Table 9.7, the results indicate that, on average, there are substantial gains to be secured by employing composite multiples models instead of single factor multiples models. The average annual IMPs, i.e. over all six industries, are indicated in the last column in Table 9.7. The range of average annual IMPs over all six industries for each of the ten years lies between 20.21% and 44.59%, which is substantial. The consistency of the outperformance of composite multiples models over single factor multiples models is evident in all the industries except for the Technology industry, where a lack of data obscured a more detailed analysis. Equally substantial gains can be secured on a per industry basis over the ten-year period, with an IMP range, on average, of between 10.12% and 44.11%. With the exception of the Consumer Services industry, which secured precision gains of 10.12%, all the industries indicate gains in excess of 25%, on average.

Table 9.7: The relative valuation performance of composite multiples models and single factor multiples models over the period 2001 to 2010

			Basic Materials								Average over all six industries
Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based			
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
2001	28.29%	2.2037	6.5442	4.9565	10.2915	3.3525	4.8249	**3.0729**	5.6203	6.1918	21.06%
2002	38.37%	2.9675	5.0133	5.7735	**4.8148**	5.6562	9.3969	7.7907	7.6589	6.2514	21.31%
2003	11.79%	2.2472	5.1693	5.3511	3.3333	**2.5476**	3.5311	4.4505	7.8506	9.4665	21.19%
2004	42.23%	2.4297	5.8732	7.2742	**4.2058**	6.1338	7.3233	5.2524	16.2399	12.5038	27.32%
2005	93.14%	0.1404	2.5351	**2.0467**	2.5347	2.2519	3.7836	2.1445	2.4633	3.2804	41.62%
2006	53.09%	1.1029	**2.3513**	2.9278	3.0649	5.2614	2.9667	2.8955	3.6810	6.6666	40.32%
2007	66.88%	1.8255	**5.5118**	5.5869	7.7138	6.1202	10.1105	7.8511	7.6437	6.7516	44.59%
2008	19.63%	2.6195	3.6874	**3.2595**	4.0672	8.3314	12.6323	7.2228	6.9947	9.2043	28.17%
2009	65.75%	0.8941	3.0896	2.8063	3.7249	3.5422	6.0400	2.8823	3.7800	**2.6105**	33.30%
2010	21.92%	4.3694	6.2685	6.4048	6.8004	7.3041	11.2096	**5.5961**	12.6510	8.7770	20.21%
Average	44.11%										

			Consumer Goods								Average over all six industries
Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based			
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
2001	8.06%	0.8352	**0.9084**	1.0947	1.8760	2.3139	1.0303	3.6896	5.3919	3.4950	21.06%
2002	12.75%	2.7161	5.1131	4.4182	4.4813	**3.1132**	13.3029	6.0945	8.8623	7.8503	21.31%
2003	25.44%	1.0724	2.3524	1.5359	1.7006	1.9225	**1.4383**	6.6236	10.3583	10.5219	21.19%
2004	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	27.32%
2005	34.71%	1.1610	3.3619	3.5189	2.3632	2.4711	2.3148	3.3265	**1.7781**	1.8308	41.62%
2006	66.36%	0.2695	1.0371	**0.8010**	1.4031	1.4754	1.4157	1.3783	1.9432	1.9245	40.32%
2007	69.73%	0.1870	1.0790	1.3535	**0.6179**	1.9899	0.8371	3.1381	2.9862	2.6552	44.59%
2008	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	28.17%
2009	39.47%	0.5340	1.1103	1.5043	**0.8822**	1.9448	0.9865	8.2273	11.9197	7.3121	33.30%
2010	34.42%	0.6577	1.8914	2.5620	**1.0029**	3.0222	2.4707	1.1963	3.9992	3.2113	20.21%
Average	36.37%										

Table 9.7…continued

Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based			Average over all six industries
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
						Consumer Services					
2001	20.17%	2.9547	4.1250	3.7011	4.3253	6.3852	6.3575	14.6150	13.2680	16.7782	21.06%
2002	23.75%	3.2534	4.6117	4.2669	11.1739	8.8126	6.6104	7.2932	17.1970	6.0985	21.31%
2003	0.71%	5.1299	10.9001	11.4413	5.1668	12.4117	9.9831	12.3578	19.4455	16.9509	21.19%
2004	9.67%	5.8721	24.6975	21.2153	6.5003	37.7532	34.6677	34.7055	36.0845	32.0255	27.32%
2005	3.63%	2.7713	3.6074	4.3512	2.8756	13.3273	10.8029	14.3834	14.0915	12.6630	41.62%
2006	6.27%	6.4695	19.4570	17.2906	6.9022	28.9942	26.4894	30.7421	19.8076	24.4195	40.32%
2007	24.89%	5.2975	23.8243	23.0733	7.0531	29.0266	15.9854	20.4815	35.5288	19.8114	44.59%
2008	0.00%	4.5770	20.6837	22.4306	4.5770	21.1544	8.7847	21.3222	18.5028	18.2262	28.17%
2009	12.07%	7.0551	18.3742	19.6590	8.0232	25.1420	19.5988	25.2851	27.7110	25.0274	33.30%
2010	0.00%	7.2207	30.0320	30.0872	7.2207	33.5460	100.0802	24.0921	22.4695	100.1153	20.21%
Average	10.12%										

Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based			Average over all six industries
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
						Financials					
2001	36.09%	0.7623	2.6320	2.4886	1.1928	2.2756	3.9214	9.7925	3.3468	7.2689	21.06%
2002	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	21.31%
2003	44.94%	1.2586	2.4472	3.4129	2.8665	3.7525	2.7976	2.2857	3.1511	3.2109	21.19%
2004	56.79%	1.9196	4.4428	5.7615	4.6680	6.4145	10.6587	5.9968	5.5832	4.9267	27.32%
2005	57.57%	1.2089	2.8493	3.9831	4.2645	5.8433	9.7585	12.9558	9.4512	13.7755	41.62%
2006	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	40.32%
2007	16.94%	4.9601	8.0644	6.7577	8.9722	5.9720	15.2918	8.9355	11.1208	20.6452	44.59%
2008	41.94%	2.1776	4.5077	5.3387	5.0752	3.7504	4.9347	51.6759	53.4204	94.2764	28.17%
2009	49.96%	0.2556	1.9994	1.1635	0.5108	2.0957	3.9273	5.6618	3.4355	2.9509	33.30%
2010	5.26%	1.6199	3.8118	3.5748	1.7099	4.8967	5.0881	22.2997	21.9352	18.7326	20.21%
Average	38.69%										

Table 9.7…continued

Industrials										Average over all six industries
Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based		
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
2001	12.71%	6.2701	7.2703	**7.1829**	7.1891	8.1709	16.4474	19.5028	17.0033	16.2877	21.06%
2002	10.35%	5.0162	8.5870	9.5685	**5.5951**	10.9942	61.7373	38.5891	50.8059	66.6803	21.31%
2003	44.25%	1.8283	6.3931	5.8461	**3.2796**	6.7799	7.0002	5.6827	9.2078	8.0272	21.19%
2004	7.67%	5.1814	14.6145	12.9299	**5.6119**	12.1885	18.4969	11.3142	38.4162	31.1195	27.32%
2005	19.05%	2.3328	3.7203	4.9466	**2.8817**	6.5579	6.6701	11.2139	18.2794	12.3863	41.62%
2006	16.42%	3.8505	6.4173	7.8440	**4.6068**	16.0711	11.9855	12.9872	18.1393	12.8063	40.32%
2007	41.38%	2.6892	8.1164	10.0933	**4.5872**	8.9272	6.4741	6.2013	13.5443	9.2903	44.59%
2008	53.87%	2.3061	5.7463	6.4040	5.9050	8.1568	9.5008	6.9076	**4.9993**	6.4077	28.17%
2009	23.52%	4.7821	13.3071	15.3629	**6.2523**	8.5313	6.8114	11.4712	13.6999	17.1728	33.30%
2010	32.29%	6.9959	14.6854	14.6468	10.6773	11.8052	17.9344	**10.3326**	16.1733	16.3145	20.21%
Average	26.15%										

Technology											Average over all six industries
Years	IMP	Composite	Earnings-based			Asset-based	Dividend-based	Cash flow-based			
			PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	
2001	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	21.06%
2002	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	21.31%
2003	0.00%	1.6329	2.1175	2.7489	**1.6329**	3.9005	3.4555	3.8874	3.8274	3.7541	21.19%
2004	20.25%	1.5942	2.5252	3.5159	**1.9990**	2.5677	5.6987	3.1062	15.8156	6.3793	27.32%
2005	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	41.62%
2006	59.48%	0.5203	1.2957	1.2886	**1.2839**	3.3024	2.4078	2.8508	3.0130	2.8411	40.32%
2007	47.72%	0.7934	1.8957	2.9846	**1.5176**	3.7877	5.4507	3.2498	2.8807	6.4884	44.59%
2008	25.40%	1.5273	2.1715	2.6455	**2.0474**	3.4951	4.1484	2.4478	4.0564	3.7321	28.17%
2009	9.02%	1.6094	**1.7690**	2.1007	2.4373	2.9720	3.1899	2.3629	2.9277	2.8796	33.30%
2010	27.37%	1.1555	1.9144	2.0162	1.7775	3.5748	1.6390	2.7691	2.4646	**1.5909**	20.21%
Average	27.04%										

The superior valuation performance of composite multiples models relative to single factor multiples models can be more effectively illustrated with the help of PCA biplots. Figure 9.1, for example, depicts the valuation performance of the composite multiples models relative to that of the single factor multiples models in the Basic Materials industry over the entire period from 2001 to 2010. The composite models are depicted to the far right of the PCA biplot, confirming their consistent superior valuation performance over the period from 2001 to 2010.

Note that the axes are colour-coded. The ten pink axes reflect that composite multiples models produced more accurate valuations than single factor multiples models over all ten years between 2001 and 2010. The quality of display reading of the PCA biplot in Figure 9.1 was 75.09% and the predictivity readings fell between 0.103 and 0.934, which, apart from the years 2001 (0.103 reading) and 2006 (0.579) indicates an insignificant loss of information.

Aside from the *lp* function in the *R-package lpSolve*, the *solnp* function (in the *R-package Rsolnp*), which is specifically adept at handling non-linear optimisations, was also used to determine the optimal weights. The results from the *solnp* function indicated a similar, but higher, average annual IMP range of precision gains of between 12.65% and 66.98% over the ten-year period. On a per industry basis over the ten-year period, the IMPs, on average, ranged between 14.39% and 72.64%. All the industries indicated substantial precision gains of 30% or more, on average, with the exception of the Consumer Services industry, which indicated an average gain in valuation accuracy of 14.39%.

How do these results compare with those of the developed markets? Unfortunately, composite-related studies are limited, both in number and in scope. In addition, the industries selected in these studies seldom match the six key industries for which sufficient data was available in the South African market. The most comparable set of results was produced by Schreiner (2007), who compared a two-factor composite model over three industries in Europe and the USA. Schreiner's overall results showed that two-factor composite multiples models produced, on average, 10.86% more accurate valuations than single factor multiples models in the USA and 15.32%
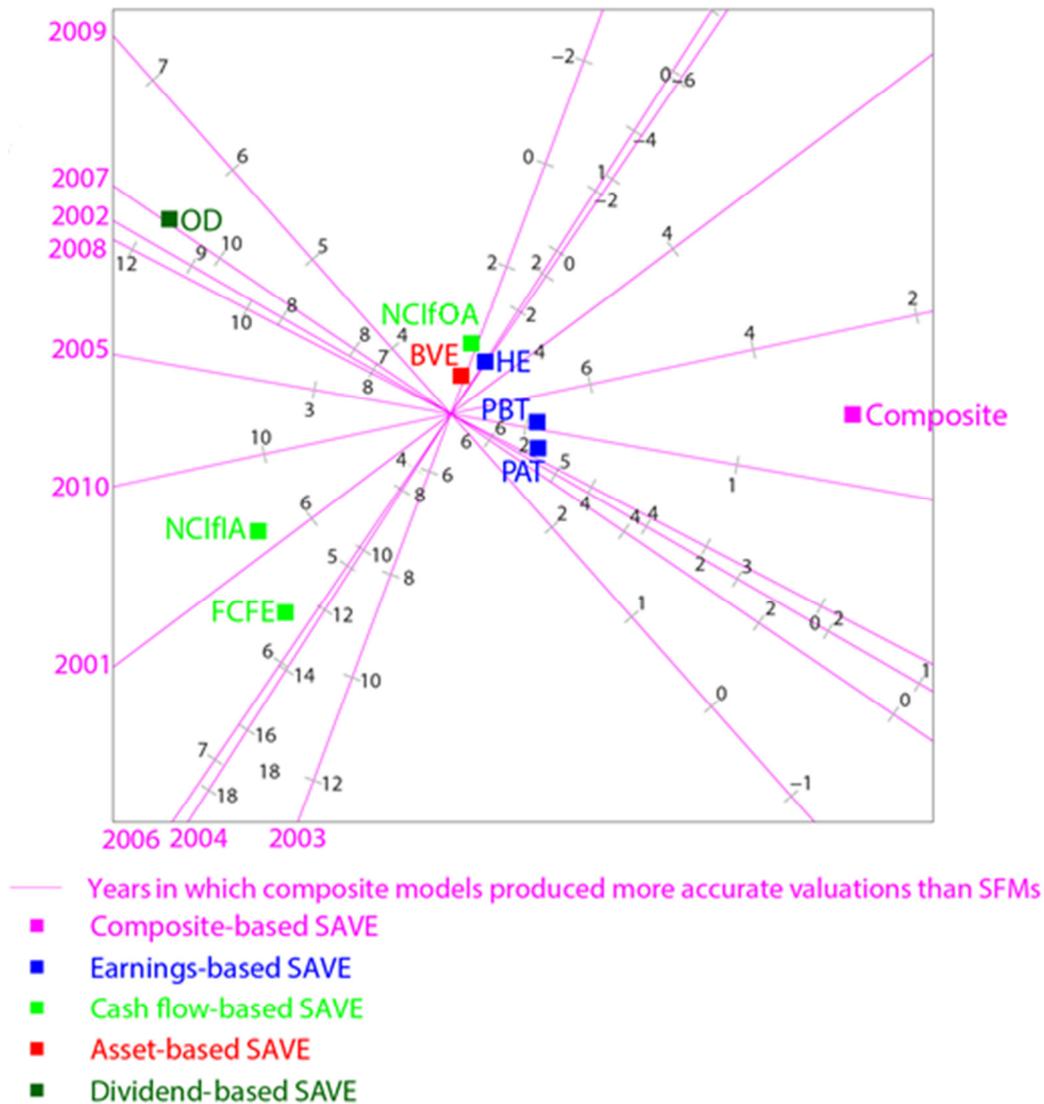
Figure 9.1: PCA biplot of the valuation performance of the composite multiples models and the equity-based single factor multiples models in the Basic Materials industry over the period 2001 to 2010

more accurate valuations in Europe. The South African results, therefore, concur with those of the developed markets, in that composite multiples models in the South African market produce more accurate valuations than single factor multiples models. From Table 9.7, it is evident that the magnitude of the improvement in valuation accuracy is more substantial in South Africa's case. Unfortunately, a more detailed comparison is not possible since none of Schreiner's selected industries correspond with any of the six key industries in the South African study.

The research results from Chapter 9 are in stark contrast with the results produced by Sehgal and Pandey (2010), who found conflicting evidence in South Africa's case. Based on the Root Mean Squared Errors method, they found that two-factor composite multiples models fail to outperform optimal single factor multiples models and, based on Theil Inequality Coefficients, they found an insubstantial improvement in valuation accuracy of 4.17%. Equally insubstantial and inconsistent results were found for the other emerging markets.

9.6   CONCLUSION

The aim of Chapter 9 was to validate H6, i.e. to determine whether industry-specific composite multiples models offer higher degrees of valuation accuracy compared to industry-specific single factor multiples models. The findings confirmed that equity-based composite multiples models produced valuations that were more accurate than those of single factor multiples models and, in so doing, answered research question six.

The study focused on equity-based multiples in particular. The results were also tested over the period between 2001 and 2010. Based on the SAVE method, the primary optimisation method that was applied (via the *lp* function in the *R-package lpSolve)* in this study, composite models, on annual average, produced between 20.21% and 44.59% more accurate valuations than single factor multiples models over the period 2001 to 2010. Although this already presents a substantial IMP range, the results obtained from the MVE method, which was applied via the *solnp* function in the *R-package Rsolnp,* indicated an even higher average annual IMP range of between 12.65% and 66.98%. However, these results were not equally consistent over all six key industries. The composite multiples models failed to offer higher degrees of valuation accuracy compared to single factor multiples models in 2008 and 2010 in the Consumer Services industry and in 2003 in the Technology industry.

An interesting phenomenon was observed regarding the valuation performance of the dividend-based value driver category. As was evident from the market- and

industry-based research findings obtained from Chapters 7 and 8, dividends produced fairly accurate valuations. However, the dividend-based value driver category, on average, secured the lowest weighting of all four value driver categories, and had particularly low component shares in the Consumer Services and Technology industries. Equally interesting was that, on a value driver category basis, the cash flow-based value driver category, which generally produced poor valuations in terms of valuation accuracy in Chapter 7, managed to secure a higher weighting than the asset- and dividend-based value driver categories, on average.

As the evidence obtained from Chapters 7 and 8 suggested, earnings-based multiples dominated the composition of the composite multiples models. Earnings-based multiples occupied, on average, between 40.90% and 89.68% of the composite models. The bulk of the earnings weighting was carried by HE, which comprised a component share of between 27.29% and 78.55%, on average. These results concur with the valuation performance of HE as a single factor multiple in Chapters 7 and 8.

The evidence therefore suggests that equity-based composite modelling may offer substantial gains in precision over single factor multiples modelling. These gains are, however, industry-specific and a *carte blanche* application thereof is ill advised. Therefore, since investment practitioners' reports typically contain various multiples, it seems prudent to consider the inclusion of composite models as a more accurate alternative.

Although the research results concur with evidence from developed capital markets, they contradict the findings from the only other study conducted on composite modelling in emerging markets. Although it is not entirely clear why the research results from Chapter 9 differ from that of the other emerging market-related study, it is possible that at least some of the discrepancies can be traced to different designs and methodologies applied in these studies.

In addition, although the superior valuation performance of equity-based composite models over equity-based single factor multiples models remains consistent over time, the composition of the composite models is not. As was the case with the value

relevance of accounting information, the composition of the composite models varies over time. This can be gleaned from the variation in the weight allocations to the respective single factor multiples contained in the composite multiples models over time, which currently limits the applicability of the composite model in practice. Additional research is required in this regard.

CHAPTER 10

CONCLUSION

10.1   SYNOPSIS OF RESEARCH CONCEPT

The objective of this study was to develop industry-specific composite multiples models for South African entities listed on the JSE, with a specific focus on six key industries. Given the keen interest of international investors in Africa as an investment destination and the popularity of multiples as a valuation approach, it was surprising to find that the construction of multiples in emerging markets, such as South Africa, is underpinned by very little empirical evidence. Consequently, in order to develop these composite multiples models, the existing multiples-based valuation theory on emerging markets, and specifically in South Africa, required expansion. This manifested in five subordinate research questions, which were investigated in Chapters 4 to 8.

Chapter 1 offered a brief background on valuations and the use of multiples in particular. It became evident that investment practitioners encounter various challenges when employing multiples for equity valuation purposes and the emerging market literature offers limited guidance in this regard. Multiples-based valuation theory was presented in Chapter 2. It was shown that multiples and DCF modelling have more in common than is generally thought. A structured approach to the construction of multiples was emphasised and a framework of 16 multiples was presented, including a discussion on the strengths and weaknesses of each. Finally, the concept of composite modelling was introduced as a logical outflow from current multiples-based valuation practice.

The research methodology and data selection process were presented in Chapter 3. The generic research design of the market-based approach was described in detail and adjustments to this generic approach were highlighted in order to clarify how the six research questions raised in Chapter 1 would be addressed. The various

statistical techniques applied in this study were discussed and deviations from the generic approach were qualified in full in each case. Methods used in addition to the market-based approach were PCA, singular value decomposition, PCR and three R-based optimisation techniques, namely *Quadprog*, *lpSolve* and *solnp*. Unfortunately, data limitations restricted the use of normal regression analysis and PCR.

The focus in Chapters 4 and 5 was on optimal peer group selection. Two methods were investigated, namely peer group selection based on industry classification and peer group selection based on valuation fundamentals.

10.2   PEER GROUP SELECTION BASED ON INDUSTRY CLASSIFICATION

The selection of an appropriate peer group is an important consideration when constructing multiples. A common approach to peer group selection, which was investigated in this study, is to group entities that reside in the same industry together, since they are thought to share similar profiles in terms of risk, growth and profitability. The valuation accuracy of the 16 multiples was compared over all four industry classifications specified on the BFA Mcgregor database, namely IND, SUP, SEC and SUB.

From the research results, it was evident that multiples whose peer groups were based on narrower industry classifications explained market values better than multiples whose peer groups were based on wider industry classifications. These findings were in line with empirical evidence from developed markets. It was established that the potential improvement in valuation accuracy that industry narrowing may offer over wider industry classifications was substantial, but that this varied, depending on the specific multiple. The P/EBITDA multiple, for example, demonstrated potential precision gains of as much as 40.19%.

The research results indicated that, on average, SEC is the optimal industry classification and that further industry narrowing to SUB added little, if any, value. This finding concurs with evidence from developed capital markets, which indicates that narrowing industry classifications beyond 3-digit codes adds little value.

However, when considering individual multiples in isolation, there may be value in narrowing the industry classification beyond the SEC level.

These findings offered an emerging market perspective on an industry-based optimal peer group selection strategy, which formed the basis for peer group selection in the remaining chapters of this dissertation. The focus in Chapter 4, however, was on peer group selection based on industry classification in particular. While the basis for peer group selection could be further refined to also consider factors other than industry classification, it is imperative that such factors are *ex ante* considerations. Therefore, since investment practitioners may be inclined to adopt more diligent approaches to peer group selection, the valuation performance of multiples whose peer groups were based on valuation fundamentals was also investigated.

10.3   PEER GROUP SELECTION BASED ON VALUATION FUNDAMENTALS

After establishing that multiples whose peer groups were based on narrower industry classifications produced more accurate valuations compared to multiples whose peer groups were based on wider industry classifications, the research focus shifted to peer group selection based on valuation fundamentals. The evidence suggested that peer group selection based on a combination of two valuation fundamentals more closely aligns entities with similar growth and risk characteristics, culminating in precision gains of as much as 71.73%.

Although RoE and Rg, on average, produced the most accurate valuations among the single valuation fundamentals, these precision gains were inconsistent and insubstantial. The valuation fundamental combination RoE.Rg produced the most accurate equity valuations among the six valuation fundamentals considered, offering an increase in valuation accuracy of as much as 37.88%, on average. It was also evident that multiples whose peer groups were based on a combination of valuation fundamentals generally outperformed multiples whose peer groups were based on industry classifications.

The results obtained from Chapter 5 offered improvements on the peer group selection strategy deduced in Chapter 4. The evidence suggests that a peer group selection strategy based on a combination of valuation fundamentals, rather than similar industry classifications, or single valuation fundamentals, offers substantial improvements in valuation accuracy.

Therefore, the research results obtained from Chapter 5 concurred with evidence from developed capital markets, which indicates that multiples whose peer groups are based on a combination of profitability and risk, or profitability and growth, yield the most accurate equity valuations. The evidence suggests that South African investment practitioners should employ a combination of valuation fundamentals for peer group selection purposes and that cognisance should be taken of the substantial precision gains offered by RoE.TA and RoE.Rg.

The evidence from Chapters 4 and 5 completed the first step in the traditional multiples-based valuation approach, which required an investigation into peer group selection. The second step in the construction of optimal single factor multiples models required an investigation into the two components of multiples, namely MPVs and value drivers.

10.4   SELECTION OF MPVs: EQUITY- AND ENTITY-BASED MULTIPLES

Evidence from Chapters 4 and 5 suggested that multiples whose peer groups were based on the RoE.Rg combination of valuation fundamentals produced the most accurate valuations. However, data limitations hindered the employment of this principle in the remaining chapters of the dissertation. Consequently, the multiples that were investigated in Chapters 6 to 9 were primarily based on the SEC industry classification. Exceptions were clearly highlighted in the text.

The focus in Chapter 6 was on two MPVs, namely MCap and MVIC. Investment practitioners often neglect to distinguish between equity- and entity-based approaches when employing multiples. In addition, limited empirical evidence exists on the relative valuation performance of equity- and entity-based multiples in

developed capital markets and the emerging market literature is entirely silent in this regard. The research results added an emerging market perspective to the debate on the valuation precision of equity- and entity-based multiples.

Despite the bias of the design of the study and valuation theory favouring entity-based multiples, equity-based multiples consistently produced more accurate valuations than their entity-based counterparts, which is in line with empirical evidence from developed capital markets. Equity-based multiples offered incremental improvements in valuation accuracy over their entity-based counterparts of as much as 12.86%.

The sub-optimal performance of entity-based multiples is attributed to noise, which is caused when the book values of preference share capital and debt are used as proxies for their respective market values. The latter distorts the accuracy of entity-based multiples. Based on the empirical evidence obtained from Chapter 6, it appears that the noise is considerable, especially when considering that the study was designed from an entity perspective and that a sub-optimal PGV was employed, which may have suppressed the magnitude of the results. After establishing that MCap-based multiples offered a higher degree of valuation accuracy, the focus for the remainder of the study shifted to the second component of multiples, namely the value drivers.

10.5   SELECTION OF VALUE DRIVERS

The modelled valuation estimates were compared to the market on an inter- and intra-value driver category basis, as well as on an individual value driver basis. The results offered an emerging market perspective on the valuation precision of all 16 value drivers and should be of particular interest to investment practitioners who are stern supporters of the use of EBITDA- and EBIT-based multiples. While all 16 value drivers proved to be value relevant, i.e. they each carried value relevant information, they exhibited various degrees of value relevancy. Equally informative was the bias tendencies that emerged from the study. This should prove insightful to investment

practitioners who opt to apply ex-model adjustments to multiples, which is a common phenomenon in the South African market.

The contribution made by Chapter 7 is that it offers an emerging market perspective on the strength of the value relevance of five value driver categories, namely earnings, dividends, assets, revenue and cash flow. The evidence suggests that earnings offer, by far, the greatest degree of valuation accuracy compared to the other four value driver categories. Compared to earnings, dividends and assets offered moderate results, while revenue and cash flow offered poor results. With the exception of revenue and cash flow, these findings concur with empirical evidence from the developed market literature. However, while the developed market literature suggests that cash flow-based value drivers produce average results, the findings in this study indicated that they produce poor results.

The consistency of the relative valuation performance of the five value driver categories was investigated over the period 2001-2010, which confirmed the initial findings. The value relevance of the five value driver categories remained fairly consistent over this period.

Given their high degree of value relevance, investment practitioners' preference for earnings-based multiples is, therefore, justified. However, the evidence rejected the general perception that cash flow-based multiples offer relatively accurate valuations compared to earnings-based multiples. As a result of the lesser degree of value relevance of cash flow-based multiples, the opportunity benefit of switching from the cash flow- to earnings-based value drivers could provide substantial precision gains of up to 30.48%.

The analysis in Chapter 7 also focused on the valuation performance of the 16 individual value drivers that resided in the five value driver categories. HE was, by far, the most accurate value driver in the earnings-based value driver category, indicating precision gains of up to 48.92%. In the cash flow-based value driver category, CgbO emerged as the most accurate value driver, offering substantial precision gains of up to 35.02%. No superior value driver emerged from the asset-

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based value driver category, as all three value drivers in this category yielded similar results.

A comparison of the valuation performances of the five best performing value drivers from each of the five value driver categories revealed that HE produced the most accurate valuations across all five value driver categories, while R produced the least accurate valuations. A sub-optimal choice of value driver carried a substantial opportunity cost of as much as 50.03%.

These results highlighted the danger of selecting individual value drivers as representatives of entire value driver categories, a bias tendency that seems to have crept up in previous research. Consequently, the valuation performance of all 16 individual value drivers was compared individually. The evidence highlighted the bias risk and indicated that there are individual value drivers that outperform their own and/or other value driver categories.

PCA biplots and optimal one-dimensional scaling were used to test the consistency of the valuation performance of the 16 individual value drivers over the period 2001-2010. The results indicated that HE consistently exhibited superior explanatory power in terms of valuation accuracy for each of the 10 years between 2001 and 2010. All three asset-based value drivers offered similar valuation performances. OD generally produced valuation errors only marginally lower than the mean over the period 2001-2010, while revenue consistently exhibited a 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 remainder of the cash flow cluster for each of the 10 years between 2001 and 2010. The worst valuation performances were undoubtedly produced by FCFE and NCIfIA, which consistently reflected significantly less value relevance compared to the other 14 value drivers.

The evidence also suggests that multiples-based modelling tends to be biased to the downside. All 16 value drivers indicated a tendency to undervalue 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, as many as two thirds of the observations exhibited a predominant tendency to undervalue share prices on the JSE. This is an important consideration for equity investment practitioners who choose to adjust their valuations outside of these models, which is a common phenomenon in practice.

Therefore, with the exception of GP, investment practitioners should scale market prices with earnings-based value drivers, specifically HE, when constructing multiples. Although EBITDA and EBIT are popular value drivers among South African investment practitioners, the evidence suggests that they are sub-optimal alternatives, which largely contradicts evidence from the developed markets. Aside from CgbO, the cash flow-based multiples offered a dismal valuation performance, i.e. they are less value relevant than earnings-based multiples, and should preferably be replaced by earnings-based multiples. Revenue also offered a poor valuation performance and should preferably be avoided.

The additional evidence gleaned from Chapters 6 and 7 made it possible to construct optimal single factor multiples models, as was the case in Chapter 7. However, the evidence from Chapters 4 to 7 was based on the market as a whole. In order to accommodate a comparison between optimal single factor multiples models and industry-specific composite multiples models, it was necessary to investigate whether the findings from Chapters 4 to 7 held equally well when subjected to an industry analysis.

10.6   INDUSTRY-SPECIFIC MULTIPLES

The analysis of the valuation performance of the 16 value drivers in Chapter 7 offered a valuable insight into their behaviour in the market as a whole. However, it was envisaged that these value drivers may behave differently in different industries. Consequently, the approach in Chapters 8 and 9 shifted from a cross-sectional analysis to an industry analysis. The evidence obtained from Chapter 8 suggested that the optimal choice of a value driver depends on the sector in which the target

entity resides and, therefore, confirmed that the valuation performance of multiples is, in fact, industry-specific.

Prior to investigating the industry-specific nature of the multiples, it was first necessary to establish which PGVs were best suited to which sectors. None of the PGVs offered evidence to suggest that they were the *de facto* optimal choice across all 28 sectors. Therefore, it was concluded that the optimal choice of PGV is also industry-specific.

The research results both confirmed and contradicted the cross-sectional-based evidence obtained from Chapter 7. As was the case in Chapter 7, the evidence indicated that multiples based on single valuation fundamentals produced the least accurate valuations across all 28 sectors. However, while the results in Chapter 7 suggested that a combination of valuation fundamentals, RoE.Rg and RoE.TA in particular, offered superior explanatory power *vis-à-vis* industry classifications, the evidence from Chapter 8 suggested a different approach. Apart from multiples whose peer groups were based on single valuation fundamentals, the remaining seven PGVs produced fairly equivalent valuations, in terms of valuation accuracy. Therefore, the superior valuation performance of multiples whose peer groups were based on a combination of valuation fundamentals, as deduced from the cross-sectional analysis conducted in Chapter 7, does not seem to hold on a per sector basis.

An SVC was subsequently created, which ranked each of the 16 equity-based multiples according to the valuation accuracy they exhibited in each of the 28 sectors. The SVC reflected substantial potential precision gains, ranging from 43.27% to 218.33% and confirmed earlier findings in Chapter 7 regarding the valuation performance of the 16 value drivers. Earnings-based value drivers dominated the top positions in the SVC, producing the most accurate valuations in 75.00% of the sectors, confirming their superior explanatory power *vis-à-vis* dividend-, asset-, revenue- and cash flow-based value drivers. Also in line with earlier findings in Chapter 7, HE was again confirmed as the most accurate individual value driver, producing the most accurate valuations in 50.00% of the sectors.

The research results therefore presented empirical evidence in support of the use of industry-specific multiples. Equally evident was that peer group selection methods are industry-specific. Investment practitioners' use of industry-specific multiples in the South African market seems well justified. However, investment practitioners should perhaps also consider more carefully their choice of PGV, since this may secure precision gains of up to 83.18%.

The research results obtained from Chapters 4 to 8 offered answers to research questions one to five, and created a theoretical platform for the construction of optimal single factor multiples models. Investment practitioners are inclined to perform multiples-based valuations based on intuition and previous experience. The value contribution of this study, as is evident from the empirical results obtained from Chapters 4 to 8, is that it provides guidance to investment practitioners in the proper construction of single factor multiples. This includes empirical support regarding two crucial decision factors when employing multiples, namely an optimal peer group selection strategy and the optimal choice of MPV and matching value driver. As such, this is the first South African study that provides extensive empirical evidence on the proper construction of single factor multiples models.

In order to achieve the objective of the study, it was then necessary to compare the valuation accuracy of the industry-specific single factor multiples models with that of the industry-specific composite multiples models.

10.7   COMPOSITE MULTIPLES MODELS

In Chapter 9 optimal equity-based composite multiples models were constructed for each of the six key industries in the South African market. Unfortunately, the nature of the data limited the depth of the final analysis. Optimal composite models were constructed based on the weight allocations as optimised by the *SAVE* function in the *R-package*. The evidence suggests that composite multiples models offer substantial improvements in valuation accuracy of up to 44.59%, on average, on an annual basis, over single factor multiples models; and that these improvements are

industry-specific. A similar increase in valuation accuracy of up to 44.11%, on average, was secured on a per industry basis.

The results suggest that value drivers from different financial statements carry incremental information content. When this content is combined, it unlocks valuation synergies that are not realised in the case of single factor multiples.

As was anticipated, earnings-based multiples, HE in particular, dominated the composition of the composite models, occupying between 40.90% and 89.68% of the component share of all the composite models, on average, over the entire period from 2001 to 2010. On the other hand, on a value driver category basis, dividends secured the lowest weighting of all four value driver categories, and had particularly low component shares in the Consumer Services and Technology industries, despite its reasonable valuation performance in Chapters 7 and 8. Equally surprising was the contribution of the cash flow-based value driver category, which, despite its relatively poor valuation performance in Chapters 7 and 8, occupied a higher weighting than assets and dividends, on average.

The evidence therefore suggests that equity-based composite multiples modelling may offer substantial gains in precision over single factor multiples modelling. These gains are, however, industry-specific and a *carte blanche* application thereof is ill advised. Therefore, since investment practitioners' reports typically contain various multiples, it seems feasible to consider including composite models as a more accurate alternative.

Note, however, that the composition of the composite models will not remain constant over time. Unfortunately, the variation in the weight allocations to the respective single factor multiples contained in the composite multiples models over time limits the applicability of the composite model in practice. Further research is required in this regard.

10.8   LIMITATIONS OF THE RESEARCH

The study does not present an exhaustive analysis of all the potential research avenues on the topic of multiples or composite modelling, in particular. Although a study of this kind invariably opens numerous additional potential research avenues, the dissertation was demarcated for the purpose of this study, based on the synopsis offered in Section 1.3. Each of Chapters 4 to 9, for example, can be explored further to contribute to a more meticulous understanding of multiples and the challenges facing the application thereof in practice, especially in emerging markets such as South Africa. Therefore, the following caveats accompany the results from this study and some of them may present future research opportunities:

- Firstly, with the initial screening of the data, observations outside the 1st and 99th percentiles were omitted. The reasoning is two-fold. One, excluding extreme observations will prevent the severe distortion of the research results and two, rational investment practitioners will most certainly exclude these extreme observations when estimating peer group multiples in practice;

- Secondly, the focus in this study was specifically on the valuation performance of trailing multiples, whose value drivers are historical in nature. Although a more comprehensive approach may also incorporate forward multiples, this is severely hamstrung by a lack of depth in the South African market, particularly at the level that the author would envisage testing them;

- Thirdly, the focus of this study was specifically on the valuation performance of multiples-based equity valuations whose peer group selection is based on the SEC industry classification. Although a more comprehensive approach may incorporate peer group selection based on valuation fundamentals, especially the inclusion of a third valuation fundamental, the lack of depth in the South African market currently does not accommodate such testing;

- Fourthly, the peer group sizes in Chapter 5 were not fixed, which accommodated the adjustment of the percentage deviation. An enhanced strategy may incorporate an investigation into an optimal deviation percentage;

- Fifthly, industry-specific multiples were constructed based on the most accurate peer group selection methods on a per sector basis. A more diligent

approach may consider industry-specific multiples based on their individual merits, rather than on the average sector-based performance.

- Finally, as is the case with all models, the market-based approach, which was adopted in this study, is not beyond reproach. The preference for the market-based approach was motivated in Section 3.3.2. An alternative approach, perhaps based on regression analysis, which accommodates the effect of endogeneity, specifically pertaining to reverse causality, could also be considered.

10.9   FUTURE RESEARCH OPPORTUNITIES

The challenges encountered during this study have highlighted numerous potential future research opportunities. The market-based research methodology applied in this study was partly the result of the peculiar nature of the data encountered in this study. It was established that the data was positively skewed, lacked sufficient depth for a more detailed analysis, did not follow a normal distribution and was non-linear. As such, the analysis of the residuals of the PCR indicated the violation of a number of standard Gauss-Markov linear assumptions. Consequently, a normal linear regression approach was not possible. A further problem was encountered with multicollinearity, which was particularly prevalent among the independent variables. Although the problem with multicollinearity was effectively dealt with by the adoption of PCA and PCR, the diagnostic analysis of the residuals indicated that key assumptions of linear regression were not satisfied. Firstly, therefore, there is scope to further enhance the research results by adopting ridge regression or another form of nonparametric analysis that is able to accommodate the issue of endogeneity. However, any such attempt will require the enhancement of the data set by imputing missing values.

Secondly, the investigation into the valuation performance of the value drivers specifically focused on trailing multiples. However, international evidence suggests that forward multiples may offer a further improvement in valuation accuracy over the top performing trailing multiples. Although this may be an interesting research topic, a comprehensive analysis in this regard will require more detailed consensus

forecasts on a wider range of value drivers. Unfortunately, this information is not available for the South African market at present.

Thirdly, the data preparation process, which, for example, omitted negative multiples from the analysis, since they are nonsensical from an economic perspective, placed further strain on the data set. A possible enhancement strategy may be investigated in the form of data imputations.

Fourthly, there is further scope to explore the topic of peer group selection based on valuation fundamentals. Unfortunately, at this stage, data limitations limited the depth of the investigation in this regard to a combination of two valuation fundamentals. A third variable could enhance the valuation accuracy even further. However, more detailed information is required in this regard. In addition, there is an opportunity to investigate the optimal peer group size by fixing the peer group deviation percentage.

Fifthly, the focus of this study was on equity-based composite models in particular, as compiled from eight equity-based multiples. Given the relatively strong valuation performance of CgbO, for example, as observed in the construction of single factor multiples models, it seems to be a promising prospect for inclusion in composite modelling. However, as was the case with equity-based composite modelling, entity-based composite modelling should adhere to the matching principle. Although no valuation approach can be regarded as an exact science, any such approach should be constructed in an internally consistent manner. Valuation models that are not constructed in an internally consistent manner are conceptually flawed and may obscure the interpretation of the results. Although entity-based composite modelling was not the focus of this dissertation, a separate research project, focused on entity-based composite modelling, may produce interesting results. These results may be of particular interest to the proponents of EBITDA- and EBIT-based multiples.

Sixthly, the weight allocations to the respective single factor multiples contained in the composite multiples models vary substantially from year to year. This, consequently, hampers the applicability of the models in practice. However, it is envisaged that a follow-up study could be conducted, based on an extended data

range, and that a bootstrapping approach can also be considered in order to observe the interaction between the various composite model constituents over a longer time frame.

Finally, it became evident at an early stage of this study that the potential magnitude of the dissertation was vast. An array of potential future research avenues emerged throughout the thesis, especially in Chapters 4 to 9, which necessitated the demarcation of these chapters. However, the theoretical issues that were addressed in Chapters 4 to 9 and which were required for the completion of this study, created a multiples-based theoretical platform for this topic for further exploration. In fact, a careful consideration of each of these chapters will reveal that they could each form research projects in their own right, especially within the scope of emerging markets. These include, but are not limited to, questions regarding the various facets of an optimal peer group selection strategy and a study of the nature of the interaction between the various constituents of the composite models.

REFERENCES

Abukari, K., Jog, V. & McConomy, B.J. 2000. *The role and the relative importance of financial statements in equity valuation.* Working paper. Ontario, Wilfred Laurier University:1-36.

Africa Progress Report. 2013. *Africa progress panel.* [Online]. Available at www.africaprogresspanel.org. Accessed:10 September 2013.

Agrawal, A. & Chadha, S. 2005. Corporate governance and accounting scandals. *Journal of Law & Economics*, 48(2):371-406.

Alford, A. 1992. The effect of the set of comparable companies on the accuracy of the price-earnings valuation method. *Journal of Accounting Research,* 30(1):94-108.

Amihud, Y., Mendelson, H. & Lauterbach, B. 1997. Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. *Journal of Financial Economics,* 45(3):365-390.

Asquith, P., Mikhail, M.B. & Au, A.S. 2005. Information content of equity analyst reports. *Journal of Financial Economics,* 75(2):245-282.

Baker, M. & Wurgler, J. 2002. Market timing and capital structure. *Journal of Finance,* 57(1):3-56.

Baker, M. & Ruback, R.S. 1999. *Estimating industry multiples.* Working paper. Cambridge, Harvard University:1-30.

Bao, B. & Chow, L. 1999. The usefulness of earnings and book value for equity valuation in emerging capital markets: evidence from listed companies in the Peoples Republic of China. *Journal of International Financial Management and Accounting,* 10(2):85-104.

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.

Barth, M.E., Beaver, W.H., Hand, J.R.M. & Landsman, W.R. 2005. Accruals, accounting-based valuation models, and the prediction of equity values. *Journal of Accounting, Auditing & Finance*, 20(4):311-345.

Bates, T.W., Lemmon, T.W. & Linck, J.S. 2006. Shareholder wealth effects and bid negotiation in freeze-out deals: Are minority shareholders left out in the cold? *Journal of Financial Economics*, 81:681-708.

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.

Berk, J. & Demarzo, P. 2007. *Corporate Finance.* 1st edition. Cape Town: Pearson Education, Inc.

Berkman, H., Bradbury, M.E. & Ferguson, J. 2000. The accuracy of price earnings and discounted cash flow methods of IPO equity valuations. *Journal of International Financial Management and Accounting,* 11(2):71-83.

Berle, A.A. & Means, G.C. 1932. Modern corporation and private property. New York: Transaction publishers.

Bernstein, W.J. 2008. *Fifty years from now.* [Online]. Available at www.efficientfrontier.com. Accessed:4 June 2013.

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.

Biddle, G.C., Bowen, R.M. & Wallace, J.S. 1999. Evidence on EVA. *Journal of Applied Corporate Finance,* 12(2):1-19.

Bildersee, J.S., Cheh, J.J. & Lee, C. 1990. The international price-earnings ratio phenomenon: a partial explanation. *Japan and the World Economy*, 2(3):263-282.

Bruner, F., Conroy, R.M., Estrada, J., Kritzman, M. & Li, W. 2002. Introduction to valuation in emerging markets. *Emerging markets review*, 3(4):300-324.

Chadda, N., McNish, R.S. & Rehm, W. 2004. All P/Es are not created equal. *McKinsey on Finance: Perspectives on Corporate Finance and Strategy,* Spring:11-15.

Chan, K. 2009. *Accounting-based composite market multiples and equity valuation.* Working paper. Sydney, University of Technology:1-70.

Chan, L.K.C., Lakonishok, J. & Sougiannis, T. 2001. The stock market valuation of research and development expenditures. *The Journal of Finance,* LVI(6):2431-2456.

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.

Collins, D.W., Pincus, M. & Xie, H. 1999. Equity valuation and negative earnings: the role of book value of equity. *The Accounting Review,* 74(1):29-61.

Copeland, T.E. 2002. What do practitioners want? *Journal of Applied Finance,* 12(1):7-14.

Correia, C., Flynn, D., Uliana, E. & Wormald, M. 2011. *Financial Management*. 7th edition. Cape Town, Juta & Company Ltd.

Courteau, L., Kao, J. & Richardson, G.D. 2001. The equivalence of dividend, cash flow and residual earnings approaches to equity valuation employing ideal terminal value calculations. *Contemporary Accounting Research,* 18(4):625-661.

Courteau, L., Kao, J., O'Keefe, T. & Richardson, G.D. 2003. *Gains to valuation accuracy of direct valuation over sector multiplier approaches.* Working paper. Turkey, Eastern Mediterranean University:1-46.

Damodaran, A. 2002. *Investment valuation: Tools and techniques for determining the value of any asset.* 2nd edition. New York, John Wiley & Sons, Inc.

Damodaran, A. 2006a. *Damodaran on valuation: Security analysis for investment and corporate finance.* 2nd edition. New Jersey, John Wiley & Sons, Inc.

Damodaran, A. 2006b. *Valuation approaches and metrics: A survey of the theory and evidence.* 2nd edition. Hanover, Now Publishers, Inc.

Damodaran, A. 2008. *Research and development expenses: Implications for profitability measurement and valuation.* Working Paper. New York, New York University:1-24.

Damodaran, A. 2009. *The dark side of valuations.* 2nd edition. New Jersey, Pearson Education, Inc.

Dellinger, R. 2010. Business valuation for the practitioner: Identifying the common area of manipulation by the valuator. *The Florida Bar Journal*, 84(8):59-65.

Dittmann, I. & Maug, E. 2008. *Biases and error measures: How to compare valuation methods.* Working paper. Rotterdam, Erasmus University:1-38.

Dittmann, I. & Weiner, C. 2005. *Selecting comparable companies for the valuation of European firms.* Working paper. Rotterdam, Erasmus University:1-25.

Durtschi, C. & Easton, P.D. 2005. Earnings management? The shapes of the frequency distributions of earnings metrics are not evidence ipso facto. *Journal of Accounting Research,* 43(4):557-592.

Easton, P.D. & Sommers, G.A. 2003. Scale and the scale effect in market-based accounting research. *Journal of Business Finance and Accounting,* 30(1&2):25-55.

Eberhart, A.C. 2001. Comparable firms and the precision of equity valuations. *Journal of Banking and Finance,* 25(7):1367-1400.

Eberhart, A.C., Maxwell, W.F. & Siddique, A.R. 2004. An examination of long-term abnormal stock returns and operating performance following R&D increases. *Journal of Finance,* 59(2):623-650.

English, J.R. 2001. *Applied equity analysis: Stock valuation techniques for Wall Street professionals.* 1st edition. New York, The McGraw-Hill Companies, Inc.

Efthimios, G.D., Strong, N.C. & Walker, M. 2004. What valuation models do analysts use? *Accounting Horizons, 18*(4):221-240.

Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance,* 25(2):383-417.

Fama, E.F. & French, K.R. 1992. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33(1):3-56.

Fama, E.F. & French, K.R. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance,* 55(1):55-84.

Fama, E.F. & Jensen, M.C. 1983. Separation of ownership and control. *Journal of Law and Economics,* 26(2):301-325.

Fenn, G.W. & Cole, R.A. 1994. Announcements of asset-quality problems and contagion effects in the life insurance industry. *Journal of Financial Economics*, 35(2):181-198.

Fernández, P. 2001. *Valuation using multiples. How do analysts reach their conclusions?* Working paper. Madrid, IESE Business School:1-13.

Fernández, P. 2002. *Valuation methods and shareholders' value creation.* 1st edition. San Diego, Academic press.

Fink, R. 2002. Tuning into cash flow. *CFO Magazine*, December:1-4.

Firer, C., Ross, S.A., Westerfield, R.W. & Jordan, B.D. 2012. *Fundamentals of Corporate Finance.* 5th edition. London, The McGraw-Hill Companies, Inc.

Fisher, D. 2013. *Valuing private companies is an art, not a science.* [Online]. Available at http: //www.forbes.com. Accessed:2 October 2013.

Foushee, S.N., Koller, T. & Mehta, A. 2012. Why bad multiples happen to good companies. *The McKinsey Quarterly,* May. New York, McKinsey & Company, Inc.:1-6.

Francis, J., Olsson, J.A. & Oswald, D. 2000. Comparing the accuracy and explainability of dividend, free cash flow and abnormal earnings equity value estimates. *Journal of Accounting Research,* 38(1):45-70.

French, N. & Gabrielli, L. 2004. The uncertainty of valuation. *Journal of Property Investment & Finance*, 22(6):484-500.

Frykman, D. & Tolleryd, J. 2010. *The Financial Times guide to corporate valuations.* 2nd edition. New Jersey, Financial Times Prentice Hall.

Fuller, R.J. & Kerr, H.S. 1981. Estimating the divisional cost of capital: An analysis of the pure-play technique. *Journal of Finance*, 36(5):997-1009.

Gabehart, S. & Brinkley, R.J. 2002. *The business valuation book.* 1st edition. New York, AMACON.

Gilson, S.C., Hotchkiss, E.S. & Ruback, R.S. 2000. Valuation of bankrupt firms. *Review of Financial Studies,* 13(70):43-74.

Glass, R.D. & Smit, E.V. 1995. the relationship between changes in money supply and changes in share prices: the semi-strong form efficiency of the Johannesburg Stock Exchange revisited. *South African Journal of Business Management*, 26(1):131-140.

Goedhart, M., Koller, T. & Wessels, D. 2005. The right role for multiples in valuation. *The McKinsey Quarterly,* March. New York, McKinsey & Company, Inc.:7-11.

Gower, J., Lubbe, S. & Le Roux, N. 2011. *Understanding Biplots.* 1st edition. Chichester, John Wiley & Sons, Ltd.

Graham, R.C. & Lefanowicz, C.E. 1999. Majority and minority ownership of publicly-traded firms: A Test of the Value of Control Using Market Multiples. *Journal of Business Finance & Accounting,* 26(1&2):171-198.

Greenacre, M. 2007. *Correspondence Analysis in Practice.* 2nd edition. London, Chapman and Hall/CRC.

Guo, R-J., Lev, B. & Shi, C. 2006. Explaining the short- and long-term IPO anomalies in US by R&D. *Journal of Business Finance and Accounting,* April/May:550-579.

Gurley, B. 2011. *All revenue is not created equal: The keys to the 10x revenue club.* [Online]. Available at. http://www.pehub.com/2011/05/bill-gurley-all-revenue-is-not-created-equal-the-keys-to-the-10x-revenue-club/. Accessed:10 July 2013.

Harrington, C. 2004. Private equity valuation: A riddle wrapped in a mystery inside an enigma. *CFA Magazine,* November:44-45.

Hartman, J.C. 2000. On the equivalence of net present value and economic value added as measures of a project's economic worth. *The Engineering Economist,* 45(2):158-165.

Hayn, C. 1995. The information content of losses. *Journal of Accounting and Economics,* 20(2):125-153.

Hendrikse, J.W. & Hendrikse, L.H. 2004. *The valuations handbook: Concepts and cases.* 1st edition. Cape Town, Lexis Nexis Butterworths.

Henschke, S. & Homburg, C. 2009. *Equity valuation using multiples: Controlling for differences between firms.* Working paper. Cologne, University of Cologne:1-38.

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

Hill, R.C., Griffiths, W.E. & Lim, G.C. 2012. *Principles of Econometrics,* 4th edition. Hoboken, New Jersey, John Wiley & Sons, Ltd.

Hou, K. & Robinson, D.T. 2006. Industry concentration and average stock returns. *Journal of Finance*, 61(4):1927-1956.

International Monetary Fund (IMF). 2012. World Economic Outlook Database, October, World Economic and Financial Surveys (IMF, Washington).

International Private Equity and Venture Capital Guidelines. 2010. [Online]. Available at www.privateequityvaluation.com. Accessed:14 March 2013.

International Private Equity and Venture Capital Guidelines. 2012. [Online]. Available at www.privateequityvaluation.com. Accessed:11 November 2013.

Ivashkovskaya, I. & Kuznetsov, I. 2007. An empirical study of country risk adjustments to market multiples in emerging markets: The case of Russia. *Выпуск,* 3:26-52.

Jefferis, K. & Smith, G. 2005. The Changing Efficiency of African Stock Markets. *South African Journal of Economics*, 73(1):54-67.

Jensen, M.C. & Meckling, W.H. 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. *Journal of Financial Economics,* 3(4):305-360.

Kamstra, M. 2003. Pricing firms on the basis of fundamentals. *Federal Reserve Bank of Atlanta: Economic Review,* First quarter:49-70.

Kaplan, S.N. & Ruback, R.S. 1995. The valuation of cash flow forecasts: An empirical analysis. *Journal of Finance*, 50(4):1059-1093.

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

Koller, T., Goedhart, M. & Wessels, D. 2005. *Valuation: Measuring and Managing the Value of Companies*. 4th edition. Hoboken, New Jersey, John Wiley & Sons, Ltd.

Kraus, A. & Litzenberger, R.H. 1973. A state-preference model of optimal financial leverage. *Journal of Finance*, 28(4):911-922.

Lang, L.H.P. & Stulz, R.M. 1992. Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics*, 32(1):45-60.

Levin, J. & Olsson, P. 2000. *Terminal value techniques in equity valuation: Implications of the steady state assumption.* Working paper. Stockholm, Stockholm School of Economics:1-26.

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. Los Angeles, University of California at Los Angeles (Anderson Graduate School of Management):1-38.

Liu, J., Nissim, D. & Thomas, J. 2007. Is cash flow king in valuations? *Financial Analysts Journal,* 63(2):1-13.

Lundholm, R. & O'Keefe, T. 2001. Reconciling value estimates from the discounted cash flow model and the residual income model. *Contemporary Accounting Research,* 18(2):311-335.

Magnusson, M.A. & Wydick, B. 2002. How efficient are Africa's emerging stock markets? *Journal of Development Studies,* 38(4):141-156.

McConnell, J.J. & Servaes, H. 1990. Additional evidence on equity ownership and corporate value, *Journal of Financial Economics*, 27(2):595-612.

McGill, R., Tukey, J.W. & Larsen, W.A. 1978. Variations of box plots. *The American Statistician*, 32(1):12-16.

Minjina, D.I. 2008. Multiples and their use for equity valuation on European capital markets. *Theoretical and Applied Economics*, 11(11):22-28.

Modigliani, F. & Miller, M.H. 1958. The cost of capital, corporation finance, and the theory of investment. *American Economic Review,* 48(3):261-297.

Modigliani, F. & Miller, M.H. 1963. Corporate income taxes and the cost of capital: A correction. *American Economic Review,* 53(3):433-443.

Mulford, C.W. & Comiskey, E.E. 2002. *The financial numbers game: Detecting creative accounting practices.* 1st edition. New York, John Wiley & Sons, Inc.

Myers, S.C. 1984. The capital structure puzzle. *Journal of Finance,* 39(3):575-592.

Myers, S.C. & Majluf, N.S. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics,* 13(2):187-221.

Negash, M. 2008. Liberalisation and the value relevance of accrual accounting information: evidence from the Johannesburg Securities Exchange. *Afro-Asian Journal of Finance and Accounting,* 1(1):81-104.

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.

Nel, W.S. 2010. A South African perspective on the multiples of choice in the valuation of ordinary shareholders' equity: From theory to practice. *African Journal of Business Management,* 4(6):930-941.

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.* European International Academic Conference proceedings. Paris, France, 9-11 June.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2013d. Multiples-based value drivers in South African context. *Risk, governance and control: Financial markets and institutions*, 3(3):35-47.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2014a. An emerging market perspective on peer group selection based on valuation fundamentals. *Applied Financial Economics,* 24(9):621-637.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2014b. Precision, consistency and bias in the South African equity market. *Journal of Economics and Behavioral Studies,* 6(5):386-399.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2014c. *The impact of an industry-specific approach to peer group selection when employing multiples to perform equity valuations.* International Conference for Academic Disciplines proceedings. Venice, Italy, 1-3 July.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2014d. *Market-based valuations in an emerging market from a biplot perspective.* International Conference on Computational Statistics proceedings. Geneva, Switzerland, 19-22 August.

Nel, W.S., Bruwer, B.W. & Le Roux, N.J. 2014e (forthcoming). An emerging market perspective on key value drivers when valuing cross-border transactions into South Africa. *Economics, Management and Financial Markets*.

Nelson, J.M. 2006. Intangible assets, book-to-market, and common stock returns. *Journal of Financial Research*, 29(1):21-41.

Nissim, D. 2011. Ratio analysis and equity valuation: *Relative Valuation of U.S. Insurance Companies.* Working paper. New York, Columbia University:1-55.

Nissim, D. & Penman, S.H. 2001. Ratio analysis and equity valuation: From research to practice. *Review of Accounting Studies,* 6(1):109-154.

Ohlson, J.A. 1995. Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research,* 11(2):661-687.

Ohlson, J.A. & Juettner-Nauroth, B. 2005. Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies,* 10(2&3):349-365.

Omran, M.F. 2003. Equity valuation using multiples in the emerging market of the United Arab Emirates. *Review of Middle East Economics and Finance,* 1(3):267-283.

Penman, S. 1998. Combining earnings and book value in equity valuation. *Contemporary Accounting Research*, 15(3):291-324.

Penman, S. & Sougiannis, T. 1998. A comparison of dividend, cash flow and earnings approaches to equity valuation. *Contemporary Accounting Research,* 15(3):343-383.

Pereiro, L.E. 2002. *Valuation of companies in emerging markets: A practical approach.* 1st edition. New York, John Wiley & Sons, Inc.

Philpott, M.F. & Firer, C. 1995. Share price anomalies and the efficiency of the JSE. *Investment Analyst Journal*, 40:39-51.

Plenborg, T. 2001. Firm valuation: Comparing the residual income and discounted cash flow approaches. *Scandinavian Journal of Management,* 18(3):303-318.

Pratt, S.P. 2005. *The market approach to valuing businesses.* 2nd edition. New Jersey, John Wiley & Sons, Inc.

Pratt, S.P. 2006. How to use transactional databases for M&A. *Business Valuation Resources,* Portland, Pacific Services, Inc.:1-11.

Pratt, S.P. & Grabowski, R.J. 2008. *Cost of capital: Applications and examples.* 3rd edition. New Jersey, John Wiley & Sons, Inc.

Pratt, S.P. & Niculita, A.V. 2007. *Valuing a business: The analysis and appraisal of closely held companies.* 5th edition. New York, The McGraw-Hill Companies, Inc.

Pretorius, D., Venter, E., Von Well, R. & Wingard, C. 2010a. *GAAP handbook: Financial Accounting and reporting practice.* Volume 1. Durban, LexisNexis.

Pretorius, D., Venter, E., Von Well, R. & Wingard, C. 2010b. *GAAP handbook: Financial Accounting and reporting practice.* Volume 2. Durban, LexisNexis.

PricewaterhouseCoopers (PwC). 2010. *Valuation Methodology Survey.* [Online]. Available at http: //www.pwc.com. Accessed:2 April 2013.

PricewaterhouseCoopers (PwC). 2012. *Getting on the right side of the delta: A deal-maker's guide to growth economies.* [Online]. Available at http: //www.pwc.com. Accessed:12 February 2014.

PricewaterhouseCoopers (PwC). 2012. *An African perspective: Valuation Methodology Survey.* 6th edition. Johannesburg, PwC Corporate Finance.

Profile. 2011. *Profile's Stock Exchange Handbook.* Johannesburg, Profile Media.

R Core Team 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Ralston, N. 2003. Overview: Equity valuation in a global context. *CFA Institute Conference Proceedings Quarterly*, April:1-3.

Rappaport, A. & Mauboussin, J.M. 2001. *The trouble with earnings and price/ earnings multiples.* [Online] Available at http://expectationsinvesting.com/pdf/earnings/pdf. Accessed:8 May 2013.

RisCura Fundamentals Analysis. 2013. *Listed multiples in Africa.* [Online]. Available at http://brightafrica.riscura.com/listed-multiples-in-africa.php. Accessed:15 August 2013.

Roosenboom, P. 2007. How do underwriters value Initial Public Offerings? An Empirical Analysis of the French IPO Market. *Contemporary Accounting Research,* 24(4):1217-1243.

Ross, S.A. 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory,* 13(3):341-360.

Schreiner, A. 2007. *Equity valuations using multiples: An empirical investigation.* PhD dissertation, Austria, University of St Gallen:1-169.

Schreiner, A. & Spremann, K. 2007. *Multiples and their valuation accuracy in European equity markets.* Working paper. Zurich, McKinsey & Company, Inc.:1-34.

Securities and Exchange Commission (SEC$_1$). 2002. *Joint meeting of SEC Regulations Committee with SEC staff.* Washington:1-7.

Sehgal, S. & Pandey, A. 2009. The behavior of price multiples in India (1990-2007). *Asian Academy of Management Journal of Finance and Accounting*, 5(1):31-65.

Sehgal, S. & Pandey, A. 2010. Equity valuation using price multiples: A comparative study for BRICKS. *Asian Journal of Finance and Accounting*, 2(1):68-91.

Smith, G. 2008. Liquidity and the informational efficiency of African stock markets. *South African Journal of Economics*, 76(2):161-175.

Smith, V.K. & Goudzwaard, M.B. 1970. Survey of investment management: Teaching and practice. *Journal of Finance,* 25:329-347.

Southern African Venture Capital and Private Equity Association. 2014. *Investing in Africa: A practical perspective for the South African institutional investor.* [Online]. Available at http: //www.savca.co.za. Accessed:19 August 2014.

Stowell, D. 2010. *An introduction to investment banks, hedge funds and private equity.* 1st edition. Burlington, Elsevier Inc.

Stumpp, P.M. 2000. *Putting EBITDA in perspective.* New York, Moody's Investor Service, Inc.:1-24.

Suozzo, P., Cooper, S., Sutherland, G. & Deng, Z. 2001. Valuation multiples: A primer. *Global equity research report,* Warburg, UBS Investment Bank:1-47.

Sweeney, R.J., Warga, A.D. & Winters, D. 1997. The market value of debt, market versus book value of debt, and returns to assets. *Financial Management*, 26(1):5-21.

Tam, P.S. & Tam, T.I. 2012. *Rethinking stock market integration: Globalization, valuation and convergence.* Working paper. Berlin, Humboldt University:1-50.

Triantis, A. 2005. Realizing the potential of real options: Does theory meet practice? *Journal of Applied Corporate Finance,* 17(2):8-16.

Upton, R.M. 1949. Conference on the teaching of business finance. *Journal of Finance,* 4(3):Summary statement.

Watson, S.A. & Rossouw, J. 2012. JSE efficiency and share price reaction to forced financial restatements. *Journal of Economic and Financial Sciences,* 5(2):417-436.

Wendt, P.F. 1966. What should we teach in an investment course? *Journal of Finance,* 21(2):416-422.

Wetherilt, A.V. & Weeken, O. 2002. Equity valuation measures: What can they tell us? *Bank of England Quarterly Bulletin,* Winter:391-403.

World Economic Forum. 2013. The Global Competitiveness Report 2012-2013, Geneva, WEF.

World Federation of Exchanges. 2014. *Statistics.* [Online]. Available at http://www.world-exchanges.org. Accessed:21 August 2014.

Wu, H., Fargher, N. & Wright, S. 2010. Accounting for investments and the relevance of losses to firm value. *The International Journal of Accounting,* 45(1):104-127.

Yee, K.K. 2004. Combining value estimates to increase accuracy. *Financial Analysts Journal,* 60(4):23-28.

Yee, K.K. 2005. Aggregation, dividend irrelevancy, and earnings-value relations. *Contemporary Accounting Research*, 22(2):453-480.

Yee, K.K. 2008. A Bayesian framework for combining valuation estimates. *Review of Quantitative Finance and Accounting,* 30(3):339-354.

Yoo, Y.K. 2006. The valuation accuracy of equity valuation using a combination of multiples. *Review of Accounting and Finance*, 5(2):108-123.

Zhang, X-J. 2000. Conservative accounting and equity valuation. *Journal of Accounting and Economics*, 29:125-149.

Annexure A: Classification of MPVs and value drivers

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 capitalisation (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.
2. Market Value of Invested Capital (MVIC) represents the value of the entity as a whole. MVIC is calculated as MCap plus preference share capital plus interest-bearing debt.

Earnings-based multiples

3. Gross Profit (GP) represents and is calculated as the difference between revenue and the cost of revenue.
4. Earnings Before Interest, Tax, Depreciation and Amortisation (EBITDA) represents an entity's earnings before interest, taxation, depreciation and amortisation. It is calculated by taking EBIT and adding back depreciation and amortisation.
5. Earnings Before Interest and Tax (EBIT) represents an entity's earnings before interest and taxation. It is calculated by taking income before-taxation and adding back interest.
6. 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.

7. 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.

8. 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.

Asset-based multiples

9. Total Assets (TA) represents 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.

10. Invested Capital (IC) represents the total cash investment by fund providers. It is calculated by deducting cash and cash equivalents from TA.

11. 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

12. Turnover (R) represents the gross revenue or revenue of the entity.

Cash flow-based multiples

13. 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.

14. 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.

15. 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.

16. Ordinary Dividends (OD) represents the amount of dividends paid to ordinary shareholders as per the cash flow statement.

17. 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.

18. 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.

Annexure B: List of respondents to the PwC survey

ABSA Capital

Acorn Private Equity

Anglo American

Argentil Capital Partners

BDO

Bravura

Brimstone

Cadiz

Coast2Coast

Co-operative Bank

Deloitte

Deutsche Bank Group

Ernst & Young

Ethos Private Equity

Grindrod Bank

HSBC Bank

I Capital advisors

Investec Corporate Finance

Java Capital

JP Morgan

KPMG

Lead Capital

Liberty Group Limited

Nedbank Capital

NIC Capital

NM Rothschild & Sons

Old Mutual Investment Group (SA)

PricewaterhouseCoopers Corporate Finance

PSG Capital

Rand Merchant Bank

Remgro

Renaissance Capital

Sanlam

Sasfin Corporate Finance

Stanbic Bank

Standard Bank

Standard Chartered

UAC of Nigeria

Annexure C: List of *R functions*

In its original form, the data extracted from the McGregor BFA database, was not suitable for the purpose of answering the six research questions. Consequently, a considerable amount of *R-coding* was done to prepare the data for the purpose of this study. In total, 32 functions were coded in the *R-package.* These functions assisted with the preparation of the data, the calculation and analysis of the valuation errors and the optimisation of the composite weightings. Note that these functions are generic. They are, therefore, not only applicable to the specific data set applied in this study but can also be applied on a different data set in other studies.

Data preparation

1. BuildNames
2. Calc.func
3. Calc.func.peergroup
4. Extract.chars
5. Form.mat.peergroup
6. har.mean
7. Keep
8. Keep.peergroup
9. Keep.peergroup.years
10. KeepPool
11. peergroup.select
12. peergroup.select.allfundamentals
13. peergroup.select.allfundamentals.years
14. peergroup.select.sevcrit
15. peergroups.combined
16. peergroups.combined.years

Valuation error calculation

17. CalcVE

18. CalcVEAll

19. CalcVEAll.peergroup

20. CalcVEAll.peergroup.years

21. CalcVEVds

22. CalcVEVds.mpv

23. CalcVEVds.mpv.peergroup

24. CalcVEVds.mpv.peergroup.years

25. CalcVEVds.peergroup

26. CalcVEVds.peergroup.years

Valuation error analysis

27. AnalyseVE

28. AnalyseVE.Fund

29. AnalyseVESigns

Optimisation

30. MinMed3

31. SAVE

32. SSVE

Annexure D: *R-code* of functions

BuildNames

```
function (charvec1=mpv.names, charvec2=vd.names)


{
# This function builds multiples.
# Inputs are MPVs and Vds
#Output: Multiples
##################################################################
temp1 <- Extract.chars(charvec1)
temp2 <- Extract.chars(charvec2)
n1 <- nrow(temp1)
n2 <- nrow(temp2)
temp12 <- paste(temp1[,1],temp1[,2],sep=".")
temp22 <- paste(temp2[,2],temp2[,3],sep=".")
paste(rep(temp12,rep(n2,n1)),temp22,sep=".")
}
```

Calc.func

```
function (mat=SEKTOR, func=mean, datvals=c("all","posnumbs"),
eps=.Machine$double.eps^(1/4))
{
# Input:
# mat is a numerical matrix
# func is the function carried out on each column of mat
# datvals is the values that are used to perform the calculations
#         There are two possibilities: "all": all the data in column are used
#                                       "posnumbs": only the pos values are used
#Output: This function does not produce output on its own. However, it is required,
and therefore called, to run the functions CalcVE and CalcVEAll
###############################################################
datval <- datvals[1]
if(is.na(match(datval,c("all","posnumbs"))))
stop("datvals must be one of (in quotes): all, posnumbs \n")
if(datval == "äll") mat<- mat
if(datval == "posnumbs") mat[mat<=eps] <- NA
n<-nrow(mat)
p<-ncol(mat)
outmat <- matrix(NA, nrow=n,ncol=p)
for(j in 1:p)
{tempvec <- mat[,j,drop=FALSE]
for(i in 1:n)
{
# xxx <- as.matrix(na.omit(tempvec[-i,1]),ncol=1)
#if(!is.na(mat[i,j])) outmat[i,j] <- func(xxx)
if(!is.na(mat[i,j])) outmat[i,j] <- func(as.vector(na.omit(tempvec[-i,1])))
else outmat[i,j] <- mat[i,j]
}
}
dimnames(outmat) <- dimnames(mat)
outmat
}
```

Calc.func.peergroup

```
function (mat, func=mean, datvals=c("all","posnumbs"),
eps=.Machine$double.eps^(1/4))
{
# Input:
# mat is a numerical matrix of the peergroup data for a given company
# func is the function that is performed on each column of mat
# datvals is the values that are used to perform the calculations
#         There are two possibilities: "all": all the data in column are used
#                                       "posnumbs": only pos values are used
# Output: This function does not produce output on its own. However, it is required,
and therefore called, to run the functions CalcVEAll.peergroup and
CalcVEAll.peergroup.years
################################################################
datval <- datvals[1]
if(is.na(match(datval,c("all","posnumbs"))))
stop("datvals must be one of (in quotes): all, posnumbs \n")
if(datval == "äll") mat<- mat
if(datval == "posnumbs") mat[mat<=eps] <- NA
n<-nrow(mat)
p<-ncol(mat)
return(apply(mat,2,function(x)func(na.omit(x))))
outmat <- matrix(NA, nrow=n,ncol=p)
for(j in 1:p)
{tempvec <- mat[,j,drop=FALSE]
for(i in 1:n)
{
if(!is.na(mat[i,j])) outmat[i,j] <- func(as.vector(na.omit(tempvec[-i,1])))
else outmat[i,j] <- mat[i,j]
}
}
dimnames(outmat) <- dimnames(mat)
outmat
}
```

Extract.chars

function (charvec=vd.names)

{

#Input: charvec is a character vector with elements of the form 'xx.yy.zz'

#Output: This function returns xx,yy,zz, which is required, and therefore called, to run

#the function BuildNames and all the functions with the prefix "Calc"

##

 temp <- lapply(charvec, function(x)unlist(strsplit(x, "\\.")))

 temp2 <- sapply(temp, function(x)length(x))

 if(any(temp2 != 3)) stop("At least one name not in form 'xx.yy.zz'\n")

 else

 t(sapply(charvec, function(x)unlist(strsplit(x, "\\."))))

}

Form.mat.peergroup

function (datlist,compname)

{

#Input: datlist is the output of Keep.peergroup

#Note: First 6 columns of each list element in datlist contains descriptive information

#sect is one of the sectors contained in datlist

Output: This function does not produce output on its own. However, it is required, and therefore called, to run all the functions with the prefix "Calc" AND which contains the term "peergroup".

##

as.matrix(datlist[[compname]][,-(1:6)])

}

har.mean

```
function (x, na.rm = TRUE,eps=.Machine$double.eps^(1/2))
{
#Input: x is a numeric matrix or vector
#Output: This function does not produce output on its own. However, it is required,
and therefore called, to run all the functions with the prefix "Calc"
################################################################
if(!is.null(ncol(x))) {if(ncol(x)>1) x <- as.matrix(x)}
                else x <- as.vector(x)
if(!is.numeric(x))stop("x must be numeric \n")
out.temp <- is.matrix(x)
out.temp <- c(out.temp,is.vector(x))
if(all(out.temp==FALSE)) stop("x must be a numeric vector or matrix \n")
################################################################
if(is.vector(x))
{
if(any(na.omit(x) <= eps))stop("Har.mean requires positive numbers only \n ")
else out <-1/ mean(1/x,na.rm=na.rm)
}
 if(is.matrix(x))
{
temp <- ifelse(is.na(x),5,x)
if(any(temp <= eps))stop("Har.mean requires positive numbers only \n ")
else out <- 1/(apply(1/x, 2, mean, na.rm = na.rm))
}
out
}
```

Keep

function (data=MCap.GP.dat, trimo=0.01,trimb=0.99,colmn="SEC", years=7:16,

num.comps=4, crit=3)

{

#Input: data is a dataframe

colmn is a group variable

##

Data are split into a list with as many elements as there are

different groups in colmn. Each element of the list is now

a dataframe with elements that are the companies in the respective groups.

##

years: numerical variable of data on which calculations have to be done

num.comps: minimum number of companies in each of the groups

crit: minimum number of years for which information is required

##

Output: A list with two components: outlist.all and outlist.selection

outlist.all: contains the data in the form of a list with dataframes of elements that

#contain information per group

outlist.selection: same as outlist.all BUT with only those groups that contain at

#least num.comps companies and with at least crit years of data

This function is required, and therefore called, to run the functions CalcVE and

CalcVEAll.

#Note: A filter is applied.

##

Data are filtered first to change values below trimo and above trimb to zeros.

tempdata <- data[,7:16]

filter <- quantile(as.vector(tempdata[tempdata>0]), probs=c(0,trimo,trimb,1), type =

4)

tempdata[tempdata < filter[2] | tempdata > filter[3]] <- 0

data[, 7:16] <- tempdata

##

create.list.groupmat <- function (X, G)

{

G an n x K indicator matrix

```
indmat.logical <- apply(G,2,function(x)as.logical(x))

K <- ncol(G)

list.groupmat <- vector("list",K)

list.groupmat<-lapply(1:K,function(y)list.groupmat[[y]]<-X[indmat.logical[,y],])

if(K == nrow(X)) for (i in 1:K) list.groupmat[[i]] <- matrix(list.groupmat[[i]],

ncol=ncol(X))

names(list.groupmat) <- colnames(G)

list.groupmat

}

indmat <- function (group.vec)

{

    elements <- levels(factor(group.vec))

    Y <- matrix(0, nrow = length(group.vec), ncol = length(elements))

    dimnames(Y) <- list(NULL, paste(elements))

    for (i in 1:length(elements)) Y[group.vec == elements[i],

      i] <- 1

    return(Y)

}

outlist.all <- create.list.groupmat(X=data, G=indmat(data[,colmn]))

b <- lapply(outlist.all,function(x)nrow(x)>=num.comps)

templist <- outlist.all[as.logical(b)]

outlist.selection <- templist

for(i in 1:length(outlist.selection))

{tempmat <- templist[[i]][, years]

 tempvec <- apply(tempmat,1,function(x) sum(x>0))

 choose <- tempvec >= crit

 outlist.selection[[i]] <- templist[[i]][choose,]

}

temp <- sapply(outlist.selection,function(x) nrow(x) >= 4)

outlist.selection <- outlist.selection[temp]

list(outlist.all = outlist.all, outlist.selection = outlist.selection)

}
```

Keep.peergroup

function (data=MCap.GP.dat, trimo=0.01, trimb=0.99,

colmn.list=peergroups.combined()$RoE.peers, years=7:16, num.comps=4, crit=3)

{

#Input: data is a dataframe

colmn.list is one of the output lists of peergroups.combined

##

Data are now split into a list with as many elements as what there

are different peergroups with at least num.comps.

List's names are the names of companies with allowable peergroups.

Each element of List forms a dataframe with the information of the respective

peergroup.

##

years: numerical variable of data on which calculations have to be performed

num.comps: minimum allowable number of companies in each of the groups

crit: minimum number of years for which information is required

##

#Output: Contains two lists of dataframes similar to the output of Keep.

Each dataframe contains the information of an allowable peergroup.

This function is required, and therefore called, to run all the functions with the

prefix "Calc" AND which contains the term "peergroup".

#Note: A filter is applied.

##

if(!identical(as.character(data[,1]) , names(colmn.list))) stop("Company names in

data and colmn.list not identical. \n")

##

Data are first filtered to change values below trimo and above trimb to zeros.

tempdata <- data[,7:16]

filter <- quantile(as.vector(tempdata[tempdata>0]), probs=c(0,trimo,trimb,1), type =

4)

tempdata[tempdata < filter[2] | tempdata > filter[3]] <- 0

data[, 7:16] <- tempdata

##

all.comp.names <- names(colmn.list)

```
comps.with.adequate.peergroupsize <- sapply(colmn.list,function(x)

length(as.character(x)) > (num.comps - 1) )

comp.use.names <- all.comp.names[comps.with.adequate.peergroupsize]

data.use <- data[comps.with.adequate.peergroupsize,]

rownames(data.use) <- comp.use.names

peergroup.list <- vector("list", length(comp.use.names))

names(peergroup.list) <- comp.use.names

for(select in comp.use.names)

 {

 names2 <- as.character(colmn.list[[select]])

 select.data <- all.comp.names %in% names2

 peergroup.list[[select]] <- data[select.data,]

 }


templist <- peergroup.list

for(i in 1:length(peergroup.list))

{tempmat <- templist[[i]][, years]

tempvec <- apply(tempmat,1,function(x) sum(x>0))

choose <- tempvec >= crit

peergroup.list[[i]] <- templist[[i]][choose,]

}

temp <- sapply(peergroup.list,function(x) nrow(x) >= 4)

list(outlist.all = peergroup.list, outlist.selection = peergroup.list[temp])

}
```

Keep.peergroup.years

function (data=MCap.GP.dat, trimo=0.01, trimb=0.99,

colmn.list=peergroups.combined.years()$years.combinedpeergroups$YR.2010$RoE

.peers,

years=7:16, num.comps=4, crit=3)

{

#Input: data is a dataframe

colmn.list is one of the output lists of peergroups.combined.years

##

Data are now split into a List with as many elements as what there

are different peergroups with at least num.comps.

List's names are the names of companies with allowable peergroups.

Each element of ListA forms a dataframe with the information of the respective

peergroup.

##

years: numerical variable of data on which calculations have to be performed

num.comps: minimum allowable number of companies in each of the groups

crit: minimum number of years for which information is required

##

#Output: Contains two lists of dataframes similar to the output of Keep.

Each dataframe contains the information of an allowable peergroup.

This function is required, and therefore called, to run all the functions with the

prefix "Calc" AND which contains the term "peergroup".

#Note: A filter is applied.

##

if(!identical(as.character(data[,1]) , names(colmn.list))) stop("Company names in

data and colmn.list not identical. \n")

##

Data are first filtered to change values below trimo and above trimb to zeros.

tempdata <- data[,7:16]

filter <- quantile(as.vector(tempdata[tempdata>0]), probs=c(0,trimo,trimb,1), type =

4)

tempdata[tempdata < filter[2] | tempdata > filter[3]] <- 0

data[, 7:16] <- tempdata

```
############################################################
all.comp.names <- names(colmn.list)
comps.with.adequate.peergroupsize <- sapply(colmn.list,function(x)
length(as.character(x)) > (num.comps - 1) )
comp.use.names <- all.comp.names[comps.with.adequate.peergroupsize]
####CHECK IF THERE IS AT LEAST ONE COMPANY WITH PEERGROUP SIZE
####AT LEAST "num.comps" ####################################
if(length(comp.use.names)==0) return(list( outlist.all=NULL, outlist.selection=NULL))
data.use <- data[comps.with.adequate.peergroupsize,]
rownames(data.use) <- comp.use.names
peergroup.list <- vector("list", length(comp.use.names))
names(peergroup.list) <- comp.use.names
for(select in comp.use.names)
 {
 names2 <- as.character(colmn.list[[select]])
 select.data <- all.comp.names %in% names2
 peergroup.list[[select]] <- data[select.data,]
 }
templist <- peergroup.list
for(i in 1:length(peergroup.list))
{tempmat <- templist[[i]][, years]
 tempvec <- apply(tempmat,1,function(x) sum(x>0))
 choose <- tempvec >= crit
 peergroup.list[[i]] <- templist[[i]][choose,]
}
temp <- sapply(peergroup.list,function(x) nrow(x) >= num.comps)
list(outlist.all = peergroup.list, outlist.selection = peergroup.list[temp])
}
```

KeepPool

```
function (data=MCap.GP.dat, colmn="SEC", years=7:16, num.comps=4, crit=3)
{
#Input: data is a dataframe
# colmn is a group variable
###############################################################
# Data are split into a list with as many elements as there are
# different groups in colmn. Each element of the list is now
# a dataframe with elements that are the companies in the respective groups.
###############################################################
# years: numerical variable of data on which calculations have to be done
# num.comps: minimum number of companies in each of the groups
# crit: minimum number of years for which information is required
###############################################################
#Output: Contains a list with two components: outlist.all and outlist.selection
# outlist.all: contains the data in the form of a list with dataframes of elements that
#contain information per group
# outlist.selection: same as outlist.all BUT with only those groups that contain at
#least num.comps companies and with at least crit years of data
#Note: No filter is applied.
###############################################################
create.list.groupmat <- function (X, G)
{
# G and n x K indicator matrix
indmat.logical <- apply(G,2,function(x)as.logical(x))
K <- ncol(G)
list.groupmat <- vector("list",K)
list.groupmat<-lapply(1:K,function(y)list.groupmat[[y]]<-X[indmat.logical[,y],])
if(K == nrow(X)) for (i in 1:K) list.groupmat[[i]] <- matrix(list.groupmat[[i]],
ncol=ncol(X))
names(list.groupmat) <- colnames(G)
list.groupmat
}
indmat <- function (group.vec)
```

```
{
    elements <- levels(factor(group.vec))
    Y <- matrix(0, nrow = length(group.vec), ncol = length(elements))
    dimnames(Y) <- list(NULL, paste(elements))
    for (i in 1:length(elements)) Y[group.vec == elements[i],
        i] <- 1
    return(Y)
}
outlist.all <- create.list.groupmat(X=data, G=indmat(data[,colmn]))


b <- lapply(outlist.all,function(x)nrow(x)>=num.comps)
templist <- outlist.all[as.logical(b)]
outlist.selection <- templist
for(i in 1:length(outlist.selection))
{tempmat <- templist[[i]][, years]
 tempvec <- apply(tempmat,1,function(x) sum(x>0))
 choose <- tempvec >= crit
 outlist.selection[[i]] <- templist[[i]][choose,]
}
temp <- sapply(outlist.selection,function(x) nrow(x) >= 4)
outlist.selection <- outlist.selection[temp]
list(outlist.all = outlist.all, outlist.selection = outlist.selection)
}
```

peergroup.select

function (fundvar = Fund.RoA.dat,percbound = 30, compvec = Fund.RoA.dat[,1],year = "2010")

{

#Input: fundvar is the fundamental variable in the form of a dataframe.

#percbound: percentage deviation from fundvar for selecting the peer group.

#compvec: vector containing names of all 395 companies (same for all fundamental

#variables).

#year: character variable indicating the year.

#Output: Upper and lower bounds of the peer group of each target company.

if (!is.character(year)) stop("Year must be character variable -- use quotes! \n")

 bounds.emp <- lapply(compvec, function(x){

 tempvalue <- percbound*fundvar[(fundvar[,1]==x), year]/100

 sort(c(fundvar[(fundvar[,1]==x), year] - tempvalue, fundvar[(fundvar[,1]==x), year] + tempvalue))

 }

)

 names(bounds.emp) <- compvec

bounds.emp is a named list containing the empirical bounds for all companies

#bounds.emp[[compvec[1]]]

peergroups <- lapply(compvec,function(x)

{

 choosevec <- fundvar[,year] >= bounds.emp[[x]][1] & fundvar[,year] <= bounds.emp[[x]][2]

temp <- compvec[choosevec]

temp[!(temp == x)]

}

)

names(peergroups) <- compvec

zero.val <- sapply(bounds.emp,function(x) all(x==0))

zero.name <- names(zero.val[zero.val])

for(i in zero.name) peergroups[[i]] <- "ZERO"

list(peergroups=peergroups,bounds.emp=bounds.emp,

```
    zero.peers=names(peergroups)[sapply(peergroups,function(x)
any(x=="ZERO"))],
      empty.peers=names(peergroups)[sapply(peergroups,function(x) length(x) ==
0)] )
#compvec[fundvar[-1, year] > bounds.emp[[1]][1] & fundvar[-1, year] <
bounds.emp[[1]][2]]
}
```

peergroup.select.allfundamentals

function (fundvar.list = list(Fund.RoA.dat=Fund.RoA.dat,

Fund.ROCE.dat=Fund.ROCE.dat, Fund.RoE.dat=Fund.RoE.dat,

 Fund.TA.dat=Fund.TA.dat, Fund.Tg.dat=Fund.Tg.dat),

 percbound = rep(30,5), compvec = Fund.RoA.dat[,1],year = "2010")

{

#Input: fundvar.list is the named list of the five fundamental variables. Each list

element is #in the form of a 395 x 16 dataframe.

#percbound: vector of length 5 = number of fundamental variables to consider.

#Element i of percbound is the percentage deviation from element i of fundvar.list for

#selecting the peer group.

Specify Inf for i-th element of percbound if fundamental variable in i-th element of

fundvar.list is not used for selecting the peer group.

#compvec: vector containing names of all 395 companies (same for all fundamental

variables).

#year: character variable indicating the year.

#Output: List of companies contained in each target company's peergroup.

#The output from this function is used as input for the function

#"peergroups.combined"

 if (!is.character(year)) stop("Year must be character variable -- use quotes! \n")

############# calculate list of empirical bounds #########

bounds.emp.list <- vector("list", length(fundvar.list))

 for(i in 1: length(fundvar.list))

 {

 bounds.emp <- lapply(compvec, function(x){

 tempvalue <- percbound[i]*fundvar.list[[i]][fundvar.list[[i]][,1]==x, year]/100

 sort(c(fundvar.list[[i]][fundvar.list[[i]][,1]==x, year] - tempvalue,

fundvar.list[[i]][fundvar.list[[i]][,1]==x, year] + tempvalue))

 }

)

 names(bounds.emp) <- compvec

 bounds.emp.list[[i]] <- bounds.emp

 }

 names(bounds.emp.list) <- names(fundvar.list)

```
###################################################################
############ bounds.emp.list is now a named list of five elements.###########
############ Each of these list elements is also a list         ################
############ containing as elements 395 empirical bounds.    ##############
###################################################################
peergroups.list <- vector("list", length(fundvar.list))
zero.val.list <- vector("list", length(fundvar.list))
empty.peers.list <- vector("list", length(fundvar.list))
names(peergroups.list) <- names(fundvar.list)
names(zero.val.list) <- names(fundvar.list)
names(empty.peers.list) <- names(fundvar.list)

for(i in 1:length(peergroups.list))
{
peergroups <- lapply(compvec,function(x)
    {
    choosevec <- (fundvar.list[[i]][,year] >= (bounds.emp.list[[i]][[x]][1])
        & fundvar.list[[i]][,year] <= (bounds.emp.list[[i]][[x]][2]))
    temp <- compvec[choosevec]
    temp[!(temp == x)]
})
zero.temp <- sapply(bounds.emp.list[[i]],function(x) all(x==0))
names(peergroups) <- compvec
peergroups.list[[i]] <- peergroups
zero.val <- names(zero.temp[zero.temp])
zero.val.list[[i]] <- zero.val
for(j in zero.val) peergroups.list[[i]][[j]] <- "ZERO"
}
for(i in 1: length(peergroups.list))
{
zero.val.list[[i]] <- names(peergroups.list[[i]])[sapply(peergroups.list[[i]],function(x)
any(x=="ZERO"))]
empty.peers.list[[i]] <-
names(peergroups.list[[i]])[sapply(peergroups.list[[i]],function(x) length(x) == 0)]
```

```
}
class(peergroups.list) <- "peergroupslist"
list(peergroups.list = peergroups.list,
    bounds.emp.list = bounds.emp.list,
     zero.peers.list = zero.val.list,
        empty.peers.list =  empty.peers.list)
}
```

peergroup.select.allfundamentals.years

```
function (fundvar.list = list(Fund.RoA.dat=Fund.RoA.dat,
Fund.ROCE.dat=Fund.ROCE.dat, Fund.RoE.dat=Fund.RoE.dat,
 Fund.TA.dat=Fund.TA.dat, Fund.Tg.dat=Fund.Tg.dat),
 percbound = rep(30,5), compvec = Fund.RoA.dat[,1],year =
c("2010","2009","2008","2007","2006","2005","2004","2003","2002","2001"))
{
#Input: fundvar.list is the named list of the five fundamental variables. Each list
element is #in the form of a 395 x 16 dataframe.
#percbound: vector of length 5 = number of fundamental variables to consider.
#Element i of percbound is the percentage deviation from element i of fundvar.list for
#selecting the peer group.
# Specify Inf for i-th element of percbound if fundamental variable in i-th element of
# fundvar.list is not used for selecting the peer group.
#compvec: vector containing names of all 395 companies (same for all fundamental
#variables).
#year: character vector indicating the years.
#The output from this function is used as input for the function
#"peergroups.combined.years"
 if (!is.character(year)) stop("Year must be a character variable -- use quotes! \n")
 years.bounds.list <- vector("list",length(year))
 names(years.bounds.list) <- paste("YR",year,sep=".")
############# Calculate list of empirical bounds. #########
tel <- 0
 for(yrin in year)
 {
tel <- tel+1
bounds.emp.list <- vector("list", length(fundvar.list))
 for(i in 1: length(fundvar.list))
 {
 bounds.emp <- lapply(compvec, function(x){
 tempvalue <- percbound[i]*fundvar.list[[i]][fundvar.list[[i]][,1]==x, yrin]/100
 sort(c(fundvar.list[[i]][fundvar.list[[i]][,1]==x, yrin] - tempvalue,
fundvar.list[[i]][fundvar.list[[i]][,1]==x, yrin] + tempvalue))
```

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```
  }
  )
 names(bounds.emp) <- compvec
 bounds.emp.list[[i]] <- bounds.emp
 }
 names(bounds.emp.list) <- names(fundvar.list)
 years.bounds.list[[tel]] <- bounds.emp.list
 }
############ bounds.emp.list is now a named list of five elements. ############
 ############ Each of these list elements is also a list       ################
 ############ containing as elements 395 empirical bounds.    ###############
 ############ The above has been calculated for each year  ################
 ############ and put in years.bounds.list                  ################
years.peergroups.list <- vector("list",length(year))
 names(years.peergroups.list) <- paste("YR",year,sep=".")
 years.zero.peers.list <- vector("list",length(year))
 names(years.zero.peers.list) <- paste("YR",year,sep=".")
 years.empty.peers.list <- vector("list",length(year))
 names(years.empty.peers.list) <- paste("YR",year,sep=".")
 tel <- 0
 for(yrin in year)
 {
tel <- tel+1
################################################################
peergroups.list <- vector("list", length(fundvar.list))
zero.val.list <- vector("list", length(fundvar.list))
empty.peers.list <- vector("list", length(fundvar.list))
names(peergroups.list) <- names(fundvar.list)
names(zero.val.list) <- names(fundvar.list)
names(empty.peers.list) <- names(fundvar.list)
for(i in 1:length(peergroups.list))
{
peergroups <- lapply(compvec,function(x)
      {
```

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```
      lower.b <- years.bounds.list[[paste("YR",yrin,sep=".")]][[i]][[x]][1]
#(bounds.emp.list[[i]][[x]][1])
      upper.b <- years.bounds.list[[paste("YR",yrin,sep=".")]][[i]][[x]][2]
#(bounds.emp.list[[i]][[x]][2])
      choosevec <- (fundvar.list[[i]][,yrin] >=  lower.b
          & fundvar.list[[i]][,yrin] <=   upper.b )
      temp <- compvec[choosevec]
      temp[!(temp == x)]
    })
zero.temp <-  sapply(years.bounds.list[[paste("YR",yrin,sep=".")]][[i]], function(x)
all(x==0))   #sapply(bounds.emp.list[[i]],function(x) all(x==0))
names(peergroups) <- compvec
peergroups.list[[i]] <- peergroups
zero.val <- names(zero.temp[zero.temp])
zero.val.list[[i]] <- zero.val
for(j in zero.val) peergroups.list[[i]][[j]] <- "ZERO"}
for(i in 1: length(peergroups.list))
{
zero.val.list[[i]] <- names(peergroups.list[[i]])[sapply(peergroups.list[[i]],function(x)
any(x=="ZERO"))]
empty.peers.list[[i]] <-
names(peergroups.list[[i]])[sapply(peergroups.list[[i]],function(x) length(x) == 0)]
}
class(peergroups.list) <- "peergroupslist"
##############################################################
years.peergroups.list[[tel]] <- peergroups.list
years.zero.peers.list[[tel]] <- zero.val.list
years.empty.peers.list[[tel]] <- empty.peers.list
}
list(years.peergroups.list = years.peergroups.list,
    years.bounds.emp.list = years.bounds.list,
    years.zero.val.peers.list = years.zero.peers.list,
      years.empty.peers.list =  years.empty.peers.list)
}
```

peergroup.select.sevcrit

```
function (fundvar = Fund.RoA.dat,percbound = 30, compvec = Fund.RoA.dat[,1],year
= "2010")
{
#Input:fundvar is the fundamental variable in the form of a dataframe.
#percbound: percentage deviation from fundvar for selecting the peer group.
#compvec: vector containing names of all 395 companies (same for all fundamental
#variables).
#year: character variable indicating the year.
 if (!is.character(year)) stop("Year must be character variable -- use quotes! \n")
 bounds.emp <- lapply(compvec, function(x){
 tempvalue <- percbound*fundvar[(fundvar[,1]==x), year]/100
 sort(c(fundvar[(fundvar[,1]==x), year] - tempvalue, fundvar[(fundvar[,1]==x), year] +
tempvalue) ) } )
 names(bounds.emp) <- compvec
# bounds.emp is a named list containing the empirical bounds for all companies
#bounds.emp[[compvec[1]]]
peergroups <- lapply(compvec,function(x)
{choosevec <- fundvar[,year] >= bounds.emp[[x]][1] & fundvar[,year] <=
bounds.emp[[x]][2]
temp <- compvec[choosevec]
temp[!(temp == x)] } )
names(peergroups) <- compvec
zero.val <- sapply(bounds.emp,function(x) all(x==0))
zero.name <- names(zero.val[zero.val])
for(i in zero.name) peergroups[[i]] <- "ZERO"
list(peergroups=peergroups,bounds.emp=bounds.emp,
    zero.peers=names(peergroups)[sapply(peergroups,function(x)
any(x=="ZERO"))],
      empty.peers=names(peergroups)[sapply(peergroups,function(x) length(x) ==
0)] )
#compvec[fundvar[-1, year] > bounds.emp[[1]][1] & fundvar[-1, year] <
bounds.emp[[1]][2]]
}
```

peergroups.combined

```
function (inputlist = peergroup.select.allfundamentals()$peergroups.list)
{
#Input: imputlist is the peergroups.list from the output of the function
#peergroup.select.allfundamentals
#Output: The peergroups of target companies based on various combinations of the
#valuation fundamentals
if(class(inputlist) != "peergroupslist") stop("Object inputlist must be of form
output$peergroups of peergroup.select.allfundamentals. \n")
combinedpeergroups.list <- vector("list",7)
names(combinedpeergroups.list) <- c("RoE.peers", "TA.peers", "Tg.peers",
"RoE_TA.peers", "RoE_Tg.peers", "TA_Tg.peers",  "RoE_TA_Tg.peers")
temp1 <- inputlist[["Fund.RoE.dat"]]
temp2 <- inputlist[["Fund.TA.dat"]]
temp3 <- inputlist[["Fund.Tg.dat"]]
compnames <- names(temp1)
temp1_2 <- lapply(compnames, function(x) temp1[[x]][temp1[[x]] %in% temp2[[x]]])
temp1_3 <- lapply(compnames, function(x) temp1[[x]][temp1[[x]] %in% temp3[[x]]])
temp2_3 <- lapply(compnames, function(x) temp2[[x]][temp2[[x]] %in% temp3[[x]]])
names(temp1_2) <- compnames
names(temp1_3) <- compnames
names(temp2_3) <- compnames
temp1_2_3 <- lapply(compnames, function(x) temp1_2[[x]][temp1_2[[x]] %in%
temp3[[x]]])
names(temp1_2_3) <- compnames
combinedpeergroups.list[["RoE.peers"]] <- temp1
combinedpeergroups.list[["TA.peers"]] <- temp2
combinedpeergroups.list[["Tg.peers"]] <- temp3
combinedpeergroups.list[["RoE_TA.peers"]] <- temp1_2
combinedpeergroups.list[["RoE_Tg.peers"]] <- temp1_3
combinedpeergroups.list[["TA_Tg.peers"]] <- temp2_3
combinedpeergroups.list[["RoE_TA_Tg.peers"]] <- temp1_2_3
combinedpeergroups.list
}
```

peergroups.combined.years

function (years.inputlist =

peergroup.select.allfundamentals.years()$years.peergroups.list)

{

#Input: years.inputlist is the years.peergroups.list from the output of the function

#peergroup.select.allfundamentals.years

#Output: The peergroups of target companies based on various combinations of the

#valuation fundamentals on an annual basis

years.combinedpeergroups <- vector("list", length(years.inputlist))

names(years.combinedpeergroups) <- names(years.inputlist)

for(yrin in names(years.inputlist))

{

inputlist <- years.inputlist[[yrin]]

if(class(inputlist) != "peergroupslist") stop("Object inputlist must be of form

output$peergroups of peergroup.select.allfundamentals. \n")

combinedpeergroups.list <- vector("list",7)

names(combinedpeergroups.list) <- c("RoE.peers", "TA.peers", "Tg.peers",

"RoE_TA.peers", "RoE_Tg.peers", "TA_Tg.peers", "RoE_TA_Tg.peers")

temp1 <- inputlist[["Fund.RoE.dat"]]

temp2 <- inputlist[["Fund.TA.dat"]]

temp3 <- inputlist[["Fund.Tg.dat"]]

compnames <- names(temp1)

temp1_2 <- lapply(compnames, function(x) temp1[[x]][temp1[[x]] %in% temp2[[x]]])

temp1_3 <- lapply(compnames, function(x) temp1[[x]][temp1[[x]] %in% temp3[[x]]])

temp2_3 <- lapply(compnames, function(x) temp2[[x]][temp2[[x]] %in% temp3[[x]]])

names(temp1_2) <- compnames

names(temp1_3) <- compnames

names(temp2_3) <- compnames

temp1_2_3 <- lapply(compnames, function(x) temp1_2[[x]][temp1_2[[x]] %in%

temp3[[x]]])

names(temp1_2_3) <- compnames

combinedpeergroups.list[["RoE.peers"]] <- temp1

combinedpeergroups.list[["TA.peers"]] <- temp2

combinedpeergroups.list[["Tg.peers"]] <- temp3

```
combinedpeergroups.list[["RoE_TA.peers"]] <- temp1_2
combinedpeergroups.list[["RoE_Tg.peers"]] <- temp1_3
combinedpeergroups.list[["TA_Tg.peers"]] <- temp2_3
combinedpeergroups.list[["RoE_TA_Tg.peers"]] <- temp1_2_3
 years.combinedpeergroups[[yrin]] <-combinedpeergroups.list
}
 list(years.combinedpeergroups = years.combinedpeergroups)
}
```

CalcVE

```
function (mult = MCap.GP.dat,vd = Vd.GP.dat, mpv = MCap.dat,
RD = 0,
sectA = "SEC", sectB= "Travel&Leisure", yrs = 7:16, crit = 3,
numcomp = 4, fun = har.mean, data = "posnumbs", unit = 1)
##############################################################
{
#Input: mult is the specific multiple for which valuation errors are calculated
#vd is the specific Vd that the MPV is scaled with
#mpv is the specific MPV that is scaled by Vd
#RD is the related debt level applied in the MPV calculation
#sectA is the basis for peer group selection that is applied
#sectB is the specific sector for which valuation errors are calculated
#yrs is the columns for which valuation errors are calculated
#crit is the number of profitable years considered for inclusion
#numcomp is the number of companies required per sectA for inclusion
#fun is the function applied for peer group selection purposes
#data is filtered to only display positive numbers
#unit is a unit measure for the data
#Output: Multiple-specific valuation errors per industry classification
Keep.out <- Keep(data = mult, colmn = sectA, years = yrs,
            num.comps = numcomp, crit=crit)
inputmat<- Form.mat(Keep.out$outlist.selection, sectB)

temp1 <- Calc.func(mat = inputmat, func = fun, datvals = data)
temp2 <-vd[rownames(temp1),-(1:6)]*unit
m.hat <- temp1*temp2

if (any(RD != 0))
 {
 if(nrow(RD) != nrow(vd))
  { warning("RD has incorrect number of rows \n")
  return(list(nrow.vd = nrow(vd), nrow.RD = nrow(RD)))
  }
```

```
RD <- RD[rownames(temp1),-(1:6)]
test1 <- dim(m.hat)
 test2 <- dim(RD)
 if (any(test1 != test2)) stop("RD not of correct size \n")
}
m <- mpv[rownames(temp1),-(1:6)]
answer <- (m.hat-RD-m)/m
 ticksym <- mult[rownames(temp1),1]
rownames(answer)<- ticksym
round(answer,digits=4)
}
```

CalcVEAll

```
function (mult = MCap.GP.dat,vd = Vd.GP.dat, mpv = MCap.dat,
RD=0,sectA = "SEC", yrs = 7:16, crit = 3,
numcomp = 4, fun = har.mean, data = "posnumbs", unit = 1, trimo=0,trimb=1)
#################################################################
{
#Input: mult is the specific multiple for which valuation errors are calculated
#vd is the specific Vd that the MPV is scaled with
#mpv is the specific MPV that is scaled by Vd
#RD is the related debt level applied in the MPV calculation
#sectA is the basis for peer group selection that is applied
#yrs is the columns for which valuation errors are calculated
#crit is the number of profitable years considered for inclusion
#numcomp is the number of companies required per sectA for inclusion
#fun is the function applied for peer group selection purposes
#data is filtered to only display positive numbers
#unit is a unit measure for the data
#trimo is used to eliminate outliers at the lower end of the multiples
#trimb is used to eliminate outliers at the top end of the multiples
#Output: The cross-multiple valuation errors per industry classification
#First check if rownumbers of RD are exactly equal to those of Vd.#############
if (any(RD != 0))
{
    if(nrow(RD) != nrow(vd))
    { warning("RD has incorrect number of rows \n")
     return(list(nrow.vd = nrow(vd), nrow.RD = nrow(RD)))
    }
}
#################################################################
Keep.out <- Keep(data = mult, colmn = sectA, years = yrs,
            num.comps = numcomp, crit=crit, trimo = trimo, trimb=trimb)
sectB <- names(Keep.out$outlist.selection)
outlist <- vector("list", length(sectB))
names(outlist) <- sectB
```

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```
i <- 0

for(name in sectB)

{

i <- i+1

inputmat<- Form.mat(Keep.out$outlist.selection, name)

temp1 <- Calc.func(mat = inputmat, func = fun, datvals = data)

temp2 <-vd[rownames(temp1),-(1:6)]*unit

m.hat <- temp1*temp2

if (any(RD != 0))

 {

 RD.temp <- RD[rownames(temp1),-(1:6)]

 test1 <- dim(m.hat)

  test2 <- dim(RD.temp)

  if (any(test1 != test2)) stop("RD.temp not of correct size \n")

 }

else RD.temp <- 0

m <- mpv[rownames(temp1),-(1:6)]

###########If MCAP =0 then m.hat - RD =0 ####################

if(any(m == 0))

{

term1 <- m.hat-RD.temp

tempmat <- m==0

term1[tempmat] <- 0

answer <- (term1-m)/m

}

###############################################################

else answer <- (m.hat-RD.temp-m)/m

 ticksym <- mult[rownames(temp1),1]

rownames(answer)<- ticksym

outlist[[i]] <- round(answer,digits=4)

}

outlist

}
```

CalcVEAll.peergroup

```
function (mult = MCap.GP.dat,vd = Vd.GP.dat, mpv = MCap.dat,
RD=0, FundamentalVarList = peergroups.combined()$RoE.peers, yrs = 7:16, crit =
3, numcomp = 4, fun = har.mean, data = "posnumbs", unit = 1,
trimo=0.01,trimb=0.99)
##############################################################################
{
#Input: mult is the specific multiple for which valuation errors are calculated
#vd is the specific Vd that the MPV is scaled with
#mpv is the specific MPV that is scaled by Vd
#RD is the related debt level applied in the MPV calculation
#FundamentalVarList: one of the seven output lists of the function
#"peergroups.combined"
#yrs is the columns for which valuation errors are calculated
#crit is the number of profitable years considered for inclusion
#numcomp is the number of companies required per sectA for inclusion
#fun is the function applied for peer group selection purposes
#data is filtered to only display positive numbers
#unit is a unit measure for the data
#trimo is used to eliminate outliers at the lower end of the multiples
#trimb is used to eliminate outliers at the top end of the multiples
#Output: The multiple-specific valuation errors per peer group specification
#First check if rownumbers of RD are exactly equal to those of Vd.##############
if (any(RD != 0))
{
   if(nrow(RD) != nrow(vd))
   { warning("RD has incorrect number of rows \n")
    return(list(nrow.vd = nrow(vd), nrow.RD = nrow(RD)))
   }
}
##############################################################################
Keep.out <- Keep.peergroup(data = mult, colmn.list = FundamentalVarList, years =
yrs,
              num.comps = numcomp, crit=crit, trimo = trimo, trimb=trimb)
```

```
sectB <- names(Keep.out$outlist.selection)
#outmat <- matrix(NA, nrow=length(sectB), ncol=length(yrs))
#dimnames(outmat) <- list(sectB, (colnames(mult))[yrs])
outmat <- NULL
for(name in sectB)
{
inputmat<- Form.mat.peergroup(Keep.out$outlist.selection, name)
temp1 <- Calc.func.peergroup(mat = inputmat, func = fun, datvals = data)
temp2 <-vd[vd[,1]==name,-(1:6)]*unit
temp2 <- unlist(ifelse(temp2==0,NA,temp2))
m.hat <- temp1*temp2
#####################################
if (any(RD != 0))
 {
 RD.temp <- RD[RD[,1]==name,-(1:6)]
 test1 <- length(m.hat)
  test2 <- length(RD.temp)
  if (any(test1 != test2)) stop("RD.temp not of correct size \n")
 }
else RD.temp <- 0
m <- mpv[mpv[,1] == name,-(1:6)]
###########If MCAP =0 then m.hat - RD =0 ###################
if(any(m == 0))
{
term1 <- m.hat-RD.temp
tempmat <- m==0
term1[tempmat] <- 0
answer <- (term1-m)/m
}
#############################################################
else answer <-(m.hat-RD.temp-m)/m
# ticksym <- mult[rownames(temp1),1]
#ticksym <- name
#rownames(answer)<- ticksym
```

```
tempmat <- matrix(round(answer,digits=4),nrow=1,ncol=length(yrs))

outmat <- rbind(outmat,tempmat)

}

dimnames(outmat) <- list(sectB, (colnames(mult))[yrs])

outmat

}
```

CalcVEAll.peergroup.years

function (mult = MCap.GP.dat,vd = Vd.GP.dat, mpv = MCap.dat,

RD=0, combined.peergroups.allyears =

out.peergroups.combined.years$years.combinedpeergroups,

FundamentalVarListName = "RoE.peers",

yrs = 7:16, crit = 3,

numcomp = 4, fun = har.mean, data = "posnumbs", unit = 1, trimo=0.01,trimb=0.99)

##

{

#Input: mult is the specific multiple for which valuation errors are calculated

#vd is the specific Vd that the MPV is scaled with

#mpv is the specific MPV that is scaled by Vd

#RD is the related debt level applied in the MPV calculation

#combined.peergroups.allyears is the output from the function

"peergroups.combined.years"

#FundamentalVarList: one of the seven output lists of the function

#"peergroups.combined.years"

#yrs is the columns for which valuation errors are calculated

#crit is the number of profitable years considered for inclusion

#numcomp is the number of companies required per sectA for inclusion

#fun is the function applied for peer group selection purposes

#data is filtered to only display positive numbers

#unit is a unit measure for the data

#trimo is used to eliminate outliers at the lower end of the multiples

#trimb is used to eliminate outliers at the top end of the multiples

#Output: The multiple-specific valuation errors per peer group specification

#First check if rownumbers of RD are exactly equal to those of Vd.#############

#combined.peergroups.allyears: contains for each year seven sublists of

#peergroups for combinations of fundamental variables.

FundamentalVarList.list <- vector("list", length(yrs))

names(FundamentalVarList.list) <- names(combined.peergroups.allyears)

names above: "YR.2010" , ... "YR.2001"

 for (i in names(combined.peergroups.allyears))

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```
 FundamentalVarList.list[[i]] <-
combined.peergroups.allyears[[i]][[FundamentalVarListName]]
# FundamentalVarList.list: For each year of the seven output lists (namely
FundamentalVarListName)
# of the function peergroups.combined.years
#First check if rownumbers of RD are exactly equal to those of Vd.#############
if (any(RD != 0))
{
   if(nrow(RD) != nrow(vd))
   { warning("RD has incorrect number of rows \n")
    return(list(nrow.vd = nrow(vd), nrow.RD = nrow(RD)))
   }
}
#############################################################
# CALL Keep.peergroup.years
#############################################################
out.list <- vector("list", length(combined.peergroups.allyears))
names(out.list) <- names(combined.peergroups.allyears)
out.mat <- matrix(NA, nrow = nrow(mult), ncol =
length(combined.peergroups.allyears))
colnames(out.mat) <- names(combined.peergroups.allyears)
rownames(out.mat) <- mult[,1]
out.df <- as.data.frame(out.mat)
tel <- 0
for(yrin in names(combined.peergroups.allyears))
{
tel <- tel + 1
Keep.out <- Keep.peergroup.years(data = mult, colmn.list =
FundamentalVarList.list[[yrin]], years = yrs,
             num.comps = numcomp, crit=crit, trimo = trimo, trimb=trimb)
sectB <- names(Keep.out$outlist.selection)
#outmat <- matrix(NA, nrow=length(sectB), ncol=length(yrs))
#dimnames(outmat) <- list(sectB, (colnames(mult))[yrs])
for(name in sectB)
```

```
{
# CALL Form.mat.peergroup
inputmat<- Form.mat.peergroup(Keep.out$outlist.selection, name)
# CALL  Calc.func.peergroup
temp1 <- Calc.func.peergroup(mat = inputmat, func = fun, datvals = data)
temp1 <- temp1[tel]
temp2 <- vd[vd[,1]==name,-(1:6)]*unit
temp2 <-temp2[tel]
if(temp2==0) temp2 <- NA
m.hat <- temp1*temp2
####################################
if (any(RD != 0))
 { RD.temp <- RD[RD[,1]==name,tel+6]
 test1 <- length(m.hat)
  test2 <- length(RD.temp)
  if (test1 != test2) stop("RD.temp not of correct size \n") }
else RD.temp <- 0
m <- mpv[mpv[,1] == name,tel+6]
###########If MCAP =0 then m.hat - RD =0 ####################
if(any(m == 0))
{
term1 <- m.hat-RD.temp
tempmat <- m==0
term1[tempmat] <- 0
answer <- (term1-m)/m
}
##############################################################
else answer <-(m.hat-RD.temp-m)/m
answer <- round(answer,digits=4)
out.df[rownames(out.df)==name, yrin] <- answer
}
}
out.df  # Dataframe of evaluation errors with 395 rows and 10 columns.
}
```

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CalcVEVds

function(vds=Extract.chars(vd.names)[,2], mpv="MVIC.ST", mpv.b="MCap.",

RD.is.0=TRUE, unit=1, ind.def="SEC",

trimo=0,trimb=1)

{

#Input: vds is the extracted Vds

#mpv is the entity-specific MPV that is scaled by Vd

#mpv.b is the equity-specific MPV that is scaled by Vd

#RD is the related debt level applied in the MPV calculation

#unit is a unit measure for the data

#ind.def is the basis for peer group selection

#trimo is used to eliminate outliers at the lower end of the multiples

#trimb is used to eliminate outliers at the top end of the multiples

#Output: The Vd-specific and sector-specific valuation errors

if(RD.is.0) RD <- 0

else RD <- eval(parse(text=paste("RD",mpv,sep=".")))

if(mpv==mpv.b) RD <- 0

j <- 0

out <- vector("list",length(vds))

for(i in vds)

    {

    j <- j+1

    multa <- parse(text=paste(mpv,i,"dat", sep="."))

     vda <- parse(text=paste("Vd",i,"dat", sep="."))

     mpv.temp <- parse(text=paste(mpv.b,"dat", sep="."))

     out[[j]]<- CalcVEAll(mult=eval(multa[[1]]),

vd=eval(vda[[1]]),mpv=eval(mpv.temp),RD=RD,unit=unit, sectA=ind.def,

    trimo=trimo,trimb=trimb)

    }

names(out) <- vds

out

}

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CalcVEVds.mpv

function(vds.d=Extract.chars(vd.names)[,2], mpv.d=Extract.chars(mpv.names),mpv.b
="MCap.",

    ind.def="SEC", RD.is.0=TRUE,trimo=0,trimb=1)

{

#Input: vds.d is the extracted Vds

#mpv.d is the the extracted MPVs

#mpv.b is the equity-specific MPV that is scaled by Vd

#ind.def is the basis for peer group selection

#RD is the related debt level applied in the MPV calculation

#trimo is used to eliminate outliers at the lower end of the multiples

#trimb is used to eliminate outliers at the top end of the multiples

#Output: The multiple-specific and sector-specific valuation errors

NOTE the UNIT specification.

mpv <- paste(mpv.d[,1],mpv.d[,2],sep=".")

#if(RD.is.0) RD <- rep(0, length(mpv))

#else RD <- paste("RD",mpv,sep=".")

############### UNIT SPECIFICATION###############################

outlist <- vector("list", length(mpv))

names(outlist) <- mpv

for(k in 1:length(mpv))

{

if(mpv[k] == "MCap.")

outlist[[k]] <- CalcVEVds(vds=vds.d,mpv=mpv[k],unit=1, mpv.b=mpv.b,

                RD.is.0=TRUE,ind.def=ind.def,trimo=trimo,trimb=trimb)

else outlist[[k]] <- CalcVEVds(vds=vds.d,mpv=mpv[k],unit=1, mpv.b=mpv.b,

                RD.is.0=RD.is.0,ind.def=ind.def,trimo=trimo, trimb=trimb)

}

 outlist

}

CalcVEVds.mpv.peergroup

```
function(vds.d=Extract.chars(vd.names)[,2], mpv.d=Extract.chars(mpv.names),mpv.b
="MCap.",
      FUND.def = out.peergroups.combined$RoE.peers,
RD.is.0=TRUE,trimo=0.01,trimb=0.99)
{
#Input: vds.d is the extracted Vds
#mpv.d is the the extracted MPVs
#mpv.b is the equity-specific MPV that is scaled by Vd
#Fund.def is the basis for peer group selection
#RD is the related debt level applied in the MPV calculation
#trimo is used to eliminate outliers at the lower end of the multiples
#trimb is used to eliminate outliers at the top end of the multiples
#Output: The multiple-specific and valuation fundamental-specific valuation errors
# NOTE the UNIT specification
mpv <- paste(mpv.d[,1],mpv.d[,2],sep=".")
#if(RD.is.0) RD <- rep(0, length(mpv))
#else RD <- paste("RD",mpv,sep=".")
############### UNIT SPECIFICATION #############################
outlist <- vector("list", length(mpv))
names(outlist) <- mpv
for(k in 1:length(mpv))
{
if(mpv[k] == "MCap.")
outlist[[k]] <- CalcVEVds.peergroup(vds=vds.d,mpv=mpv[k],unit=1, mpv.b=mpv.b,
                    RD.is.0=TRUE,FUND.def=FUND.def,trimo=trimo,trimb=trimb)
else outlist[[k]] <- CalcVEVds.peergroup(vds=vds.d,mpv=mpv[k],unit=1,
mpv.b=mpv.b,
                      RD.is.0=RD.is.0,FUND.def=FUND.def,trimo=trimo,
trimb=trimb)
}
 outlist}
```

CalcVEVds.mpv.peergroup.years

function(vds.d=Extract.chars(vd.names)[,2], mpv.d=Extract.chars(mpv.names),mpv.b
="MCap.",

    yrs.list = out.peergroups.combined.years$years.combinedpeergroups,

        FUND.def = "RoE.peers", RD.is.0=TRUE,

        unit = 1, yrsvec = 7:16, crit = 3, numcomp = 4,

    fun = har.mean, data = "posnumbs", trimo=0.01,trimb= 0.99)

{

#Input: vds.d is the extracted Vds

#mpv.d is the the extracted MPVs

#mpv.b is the equity-specific MPV that is scaled by Vd

#yrs.lst is the output from the function peergroups.combined.years

#Fund.def is the basis for peer group selection

#RD is the related debt level applied in the MPV calculation

#unit is a unit measure for the data

#yrsvec is the columns for which valuation errors are calculated

#crit is the number of profitable years considered for inclusion

#numcomp is the number of companies required per peer group for inclusion

#fun is the function applied for peer group selection purposes

#data is filtered to only display positive numbers

#trimo is used to eliminate outliers at the lower end of the multiples

#trimb is used to eliminate outliers at the top end of the multiples

#Output: The multiple-specific and valuation fundamental-specific valuation errors

NOTE the UNIT specification.

mpv <- paste(mpv.d[,1],mpv.d[,2],sep=".")

#if(RD.is.0) RD <- rep(0, length(mpv))

#else RD <- paste("RD",mpv,sep=".")

############### UNIT SPECIFICATION ############################

outlist <- vector("list", length(mpv))

names(outlist) <- mpv

for(k in 1:length(mpv))

{

if(mpv[k] == "MCap.")

outlist[[k]] <- CalcVEVds.peergroup.years(vds=vds.d,mpv=mpv[k], mpv.b=mpv.b,

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```
                    yrs.list = yrs.list, FUND.def=FUND.def, yrsvec = yrsvec, crit=crit,
                        numcomp=numcomp, fun=fun, data = data,
RD.is.0=TRUE,unit=unit,
                        trimo=trimo,trimb=trimb)
else outlist[[k]] <- CalcVEVds.peergroup.years(vds=vds.d,mpv=mpv[k],
mpv.b=mpv.b,
            yrs.list = yrs.list, FUND.def=FUND.def, yrsvec = yrsvec, crit=crit,
                        numcomp=numcomp, fun=fun, data = data,
RD.is.0=RD.is.0,unit=unit,
                        trimo=trimo,trimb=trimb)
}
 outlist
}
```

CalcVEVds.peergroup

```
function(vds=Extract.chars(vd.names)[,2], mpv="MVIC.ST", mpv.b="MCap.",
RD.is.0=TRUE, unit=1, FUND.def=out.peergroups.combined$RoE.peers,
trimo=0.01,trimb=0.99)
{
#Input: vds is the extracted Vds
#mpv is the entity-specific MPV
#mpv.b is the equity-specific MPV that is scaled by Vd
#RD is the related debt level applied in the MPV calculation
#unit is a unit measure for the data
#Fund.def is the output from the function "peergroup.combined"
#trimo is used to eliminate outliers at the lower end of the multiples
#trimb is used to eliminate outliers at the top end of the multiples
#Output: The Vd-specific and valuation fundamental-specific valuation errors
if(RD.is.0) RD <- 0
else RD <- eval(parse(text=paste("RD",mpv,sep=".")))
if(mpv==mpv.b) RD <- 0
j <- 0
out <- vector("list",length(vds))
for(i in vds)
    {
    j <- j+1
    multa <- parse(text=paste(mpv,i,"dat", sep="."))
     vda <- parse(text=paste("Vd",i,"dat", sep="."))
     mpv.temp <- parse(text=paste(mpv.b,"dat", sep="."))
     out[[j]]<- CalcVEAll.peergroup(mult=eval(multa[[1]]),
vd=eval(vda[[1]]),mpv=eval(mpv.temp),RD=RD,unit=unit,
     FundamentalVarList = FUND.def, trimo=trimo,trimb=trimb)
    }
names(out) <- vds
out
}
```

CalcVEVds.peergroup.years

```
function(vds=Extract.chars(vd.names)[,2], mpv="MCap.", mpv.b="MCap.",
RD.is.0=TRUE, unit=1,
yrs.list = out.peergroups.combined.years$years.combinedpeergroups,
FUND.def="RoE.peers",
yrsvec = 7:16, crit = 3,  numcomp = 4, fun = har.mean, data = "posnumbs",
trimo=0.01,trimb=0.99)
{
#Input: vds is the extracted Vds
#mpv is the entity-specific MPV
#mpv.b is the equity-specific MPV that is scaled by Vd
#RD is the related debt level applied in the MPV calculation
#unit is a unit measure for the data
#yrs.list is the output from the function "peergroup.combined.years"
#Fund.def is the basis for peer group selection
#yrsvec is the columns for which valuation errors are calculated
#crit is the number of profitable years considered for inclusion
#numcomp is the number of companies required per peer group for inclusion
#fun is the function applied for peer group selection purposes
#data is filtered to only display positive numbers
#trimo is used to eliminate outliers at the lower end of the multiples
#trimb is used to eliminate outliers at the top end of the multiples
#Output: The Vd-specific and valuation fundamental-specific valuation errors on an
#annual basis
if(RD.is.0) RD <- 0
else RD <- eval(parse(text=paste("RD",mpv,sep=".")))
if(mpv==mpv.b) RD <- 0
j <- 0
out <- vector("list",length(vds))
#return(out.peergroups.combined.years$years.combinedpeergroups$YR.2010[[FUN
D.def]])
for(i in vds[1:length(vds)])
    {
    j <- j+1
```

```
      multa <- parse(text=paste(mpv,i,"dat", sep="."))
       vda <- parse(text=paste("Vd",i,"dat", sep="."))
       mpv.temp <- parse(text=paste(mpv.b,"dat", sep="."))
       out[[j]]<- CalcVEAll.peergroup.years(mult=eval(multa[[1]]),
vd=eval(vda[[1]]),mpv=eval(mpv.temp),RD = RD,
        combined.peergroups.allyears = yrs.list, FundamentalVarListName =
FUND.def,yrs = yrsvec, crit = crit, numcomp = numcomp,
       fun = fun, data = data, unit=unit, trimo=trimo,trimb=trimb)
       ##################
}
names(out) <- vds
out
}
```

AnalyseVE

```
function (p1="out199Filter.SEC.Equity", p2="MCap", p3="GP",
fun=function(x)c(n=length(na.omit(abs(x))),mean=mean(abs(x),na.rm=T),
se=sd(abs(x),na.rm=T), median=median(abs(x),na.rm=T),
mad =mad(abs(x),na.rm=T),IQR =IQR(abs(x),na.rm=T), min=min(abs(x),na.rm=T),
max=max(abs(x),na.rm=T),range =diff(range(abs(x),na.rm=T)),
"IPR 5"=diff(quantile(na.omit(abs(x)),probs=c(0.05,0.95))),
"IPR 10"=diff(quantile(na.omit(abs(x)),probs=c(0.10,0.90))),
"PER"=quantile(na.omit(abs(x)),probs=c(0.05)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.10)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.25)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.95)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.90)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.75)),
"FRE 0.15"= sum(na.omit(abs(x))<=0.15)/length(na.omit(abs(x))),
"FRE 0.25"= sum(na.omit(abs(x))<=0.25)/length(na.omit(abs(x))),
madmed=(mad(abs(x),na.rm=T)/median(abs(x),na.rm=T)),
CV=(sd(abs(x),na.rm=T)/mean(abs(x),na.rm=T))))
{
#Input: p1 is the equity- or entity-based multiple-specific output from the function
#"CalcVE.Vds.mpv"
#p2 is the MPV
#p3 is the Vd
# fun are the various statistical measures that are applied
#Output: Three outputs: raw data, out.1 and out.2
#raw data is the pooled valuation errors
# out.1 is the analysis of the valuation errors on an annual basis
# out.2 is the pooled analysis of the valuation errors
datlys <- paste(p1,p2,p3, sep="$")
datlys <- eval(parse(text=datlys))
temp.len<-length(datlys)
temp.mat <- as.matrix(datlys[[1]])
for (i in 2:temp.len)
temp.mat <- rbind(temp.mat,as.matrix(datlys[[i]]))
```

```
temp.vec <- as.vector(temp.mat)

n <- nrow(temp.mat)

out1 <- apply(temp.mat,2,FUN=fun)

out2 <- c(n=nrow(temp.vec),fun=fun(temp.vec))

list(rawdata=temp.mat,out.1=round(out1,digits=4),out.2=round(out2,digits=4))

}
```

AnalyseVE.Fund

```
function (p1="out.CalcVEVds.mpv.peergroup.years_RoE_Tg.peers", p2="MCap",
p3="GP", fun=function(x)c(n=length(na.omit(abs(x))), mean=mean(abs(x),na.rm=T),
se=sd(abs(x),na.rm=T), median=median(abs(x),na.rm=T),
mad =mad(abs(x),na.rm=T),IQR =IQR(abs(x),na.rm=T),min=min(abs(x),na.rm=T),
max=max(abs(x),na.rm=T),range =diff(range(abs(x),na.rm=T)),
"IPR 5"=diff(quantile(na.omit(abs(x)),probs=c(0.05,0.95))),
"IPR 10"=diff(quantile(na.omit(abs(x)),probs=c(0.10,0.90))),
"PER"=quantile(na.omit(abs(x)),probs=c(0.05)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.10)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.25)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.95)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.90)),
"PER"=quantile(na.omit(abs(x)),probs=c(0.75)),
"FRE 0.15"= sum(na.omit(abs(x))<=0.15)/length(na.omit(abs(x))),
"FRE 0.25"= sum(na.omit(abs(x))<=0.25)/length(na.omit(abs(x))),
madmed=(mad(abs(x),na.rm=T)/median(abs(x),na.rm=T)),
CV=(sd(abs(x),na.rm=T)/mean(abs(x),na.rm=T))))
{
#Input: p1 is the equity- or entity-based multiple-specific output from the function
#"out.CalcVEVds.mpv.peergroup.years"
#p2 is the MPV
#p3 is the Vd
# fun are the various statistical measures that are applied
#Output: Three outputs: raw data, out.1 and out.2
#raw data is the pooled valuation errors
# out.1 is the analysis of the valuation errors on an annual basis
# out.2 is the pooled analysis of the valuation errors
```

```
datlys <- paste(p1,p2,p3, sep="$")
datlys <- eval(parse(text=datlys))
#temp.len<-length(datlys)
#temp.mat <- as.matrix(datlys[[1]])
 temp.mat <- as.matrix(datlys)
#for (i in 2:temp.len)
#temp.mat <- rbind(temp.mat,as.matrix(datlys[[i]]))
temp.vec <- as.vector(temp.mat)
n <- nrow(temp.mat)
out1 <- apply(temp.mat,2,FUN=fun)
out2 <- c(n=nrow(temp.vec),fun=fun(temp.vec))
list(rawdata=temp.mat,out.1=round(out1,digits=4),out.2=round(out2,digits=4))
}
```

AnalyseVESigns

function (p1="out199Filter.SEC.Equity", p2="MCap", p3="GP",

fun=function(x)c(n=length(na.omit(x)),mean=mean(x,na.rm=T),se=sd(x,na.rm=T),

min =min(x,na.rm=T),max =max(x,na.rm=T), median=median(x,na.rm=T),

 mad =mad(x,na.rm=T),IQR =IQR(x,na.rm=T), range =diff(range(x,na.rm=T)),

"IPR 5"=diff(quantile(na.omit(x),probs=c(0.05,0.95))),

"IPR 10"=diff(quantile(na.omit(x),probs=c(0.10,0.90))),

"PER"=quantile(na.omit(x),probs=c(0.90)),"PER"=quantile(na.omit(x),probs=c(0.80)),

"PER"=quantile(na.omit(x),probs=c(0.70)),"PER"=quantile(na.omit(x),probs=c(0.69)),

"PER"=quantile(na.omit(x),probs=c(0.68)),"PER"=quantile(na.omit(x),probs=c(0.67)),

"PER"=quantile(na.omit(x),probs=c(0.66)),"PER"=quantile(na.omit(x),probs=c(0.65)),

"PER"=quantile(na.omit(x),probs=c(0.64)),"PER"=quantile(na.omit(x),probs=c(0.63)),

"PER"=quantile(na.omit(x),probs=c(0.62)),"PER"=quantile(na.omit(x),probs=c(0.61)),

"PER"=quantile(na.omit(x),probs=c(0.60)),"PER"=quantile(na.omit(x),probs=c(0.59)),

"PER"=quantile(na.omit(x),probs=c(0.58)),"PER"=quantile(na.omit(x),probs=c(0.57)),

"PER"=quantile(na.omit(x),probs=c(0.56)),"PER"=quantile(na.omit(x),probs=c(0.55)),

"PER"=quantile(na.omit(x),probs=c(0.54)),"PER"=quantile(na.omit(x),probs=c(0.53)),

"PER"=quantile(na.omit(x),probs=c(0.52)),"PER"=quantile(na.omit(x),probs=c(0.51)),

"PER"=quantile(na.omit(x),probs=c(0.50)),

"FRE 0.15"= sum(na.omit(x)<=0.15)/length(na.omit(x)),

"FRE 0.25"= sum(na.omit(x)<=0.25)/length(na.omit(x))))

{

#Input: p1 is the equity- or entity-based multiple-specific output from the function

#"CalcVE.Vds.mpv"

#p2 is the MPV

#p3 is the Vd

fun are the various statistical measures that are applied

#Output: Three outputs: raw data, out.1 and out.2

#raw data is the pooled valuation errors

out.1 is the analysis of the valuation errors on an annual basis

out.2 is the pooled analysis of the valuation errors

```
datlys <- paste(p1,p2,p3, sep="$")
datlys <- eval(parse(text=datlys))
temp.len<-length(datlys)
temp.mat <- as.matrix(datlys[[1]])
for (i in 2:temp.len)
temp.mat <- rbind(temp.mat,as.matrix(datlys[[i]]))
temp.vec <- as.vector(temp.mat)
n <- nrow(temp.mat)
out1 <- apply(temp.mat,2,FUN=fun)
out2 <- c(n=nrow(temp.vec),fun=fun(temp.vec))
list(rawdata=temp.mat,out.1=round(out1,digits=4),out.2=round(out2,digits=4))
}
```

MinMed3

```
function (yvec,xmat,startvals = rep(1/ncol(xmat), ncol(xmat)))
{
#This function is similar to function MinMed but the objective function is in
#standardised form and with specified starting values i.e. no random starts.
#The default startvalues are equal probs.
#Input: yvec is a vector of MPVs
#xmat is a matrix of value estimates
#startvals is the starting values
#Output: Two outputs of note are pars and values:
#pars are the optimised weights
#values are the valuation error associated with pars
if(length(yvec) != nrow(xmat)) stop("Number of elements of yvec must be equal to
the number of rows of xmat \n")
p <- ncol(xmat)
fun1 <- function(a, y, mat) median(abs(y-mat %*% a)/y)
# fun1: objective function that will be minimised
eqff <- function(a,y, mat) sum(a)
eqBB <- 1
# eqff and eqBB specify the equality constraint
ineqff <- function(a,y,mat) a
ineqLBB <- rep(0, p)
ineqUBB <- rep(1, p)
# ineqff, ineqLBB and ineqUBB specify the inequality constraints
#Function gosolnp of package Rsolnp used for executing the optimisation.
solnp(pars = startvals,fun = fun1, eqfun = eqff, eqB  = eqBB, ineqfun = ineqff,
ineqLB = ineqLBB, ineqUB = ineqUBB, LB = rep(0,p), UB = rep(1,p),
y = yvec, mat = xmat)
}
```

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SAVE

```
function ()
{
#SAVE code for BM.2010 output using function lp from R-package lpSolve.
data.use <- as.matrix(MCap.MHats.2010.BasicMaterials.Clean[,-
c(1:6,8:10,14,16,17:20,22)])
Mmat <- data.use[ ,-1]
MCap.vec <- data.use[ ,1]
y.vec <- MCap.vec
M.star <- sweep(Mmat, 1, y.vec, "/")
n <- nrow(M.star)
p <- ncol(M.star)
temp1 <- c(rep(1, p), rep(0, n))
temp2 <- cbind(diag(p), matrix(0, nrow=p, ncol=n))
temp3 <- cbind(M.star, diag(n))
temp4 <- cbind(M.star, -diag(n))
Cmat <- rbind(temp1, temp2, temp3, temp4)
const.dir <- c("=", rep(">=",p+n), rep("<=",n))
const.rhs <-   c(1, rep(0, p),rep(1, n), rep(1,n))
objective.in <- c(rep(0, p), rep(1, n))
out <- lp("min", objective.in, const.mat=Cmat,const.dir, const.rhs)
out
out$solution
out$objval
out$solution[1:6]
sum(round(out$solution[1:6],digits=4))
}
```

SSVE

function ()

{

#SSVE code for BM.2010 output using function *solve.QP* from *R-package Quadprog*.


```
Qprog.data <- MCap.MHats.2008.BasicMaterials.Clean
Qprog.data <- log( as.matrix(Qprog.data[,-1]))
Qprog.data <- Qprog.data[,-c(2:4,8,10:14,16)]
H <- Qprog.data[,-1] # Log of value drivers.
y <- Qprog.data[,1] #Log of MCap.
dvec <- t(H) %*% y
Dmat <- t(H) %*% H
bvec <- c(1,rep(0,6))
Amat <- cbind(1, diag(6))
BM.2008 <- solve.QP(Dmat,dvec,Amat,bvec,meq=1)
BM.2008
}
```

Annexure E: Correlation matrices

Correlation matrices of the 16 value drivers over the period 2001 to 2010

GP

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9648	1.0000								
2008	0.9259	0.9556	1.0000							
2007	0.9177	0.9494	0.9682	1.0000						
2006	0.9136	0.9329	0.9511	0.9592	1.0000					
2005	0.8930	0.9108	0.9240	0.9534	0.9827	1.0000				
2004	0.8875	0.9122	0.9011	0.9339	0.9370	0.9602	1.0000			
2003	0.8913	0.9039	0.8669	0.9185	0.9009	0.9466	0.9554	1.0000		
2002	0.8201	0.8321	0.8043	0.8608	0.8914	0.9369	0.9429	0.9691	1.0000	
2001	0.8389	0.8479	0.8298	0.8719	0.8714	0.9003	0.9055	0.9318	0.9282	1.0000

EBITDA

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9528	1.0000								
2008	0.9282	0.9423	1.0000							
2007	0.9410	0.9100	0.9651	1.0000						
2006	0.9232	0.8777	0.9315	0.9635	1.0000					
2005	0.9004	0.8619	0.8990	0.9310	0.9542	1.0000				
2004	0.9095	0.8638	0.8902	0.9101	0.9181	0.9670	1.0000			
2003	0.8996	0.8810	0.8835	0.9075	0.8986	0.9527	0.9611	1.0000		
2002	0.8767	0.8268	0.8414	0.8902	0.8824	0.9082	0.9154	0.9457	1.0000	
2001	0.8920	0.8445	0.8447	0.8811	0.8698	0.9175	0.8985	0.9150	0.9316	1.0000

EBIT

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9595	1.0000								
2008	0.9380	0.9412	1.0000							
2007	0.9502	0.9184	0.9665	1.0000						
2006	0.9306	0.8633	0.9333	0.9613	1.0000					
2005	0.9058	0.8738	0.9078	0.9284	0.9483	1.0000				
2004	0.8976	0.8606	0.8854	0.8963	0.9083	0.9579	1.0000			
2003	0.9019	0.8726	0.8749	0.8989	0.8963	0.9158	0.9559	1.0000		
2002	0.8872	0.8370	0.8657	0.9100	0.9048	0.9160	0.9202	0.9460	1.0000	
2001	0.8771	0.8381	0.8332	0.8685	0.8586	0.8809	0.8650	0.8856	0.9154	1.0000

PAT

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9276	1.0000								
2008	0.9032	0.9157	1.0000							
2007	0.9044	0.9194	0.9355	1.0000						
2006	0.8741	0.8597	0.8866	0.9413	1.0000					
2005	0.8527	0.8769	0.8744	0.9113	0.9410	1.0000				
2004	0.8675	0.8455	0.8690	0.8903	0.9051	0.9435	1.0000			
2003	0.8434	0.8272	0.8332	0.8806	0.8783	0.9064	0.9264	1.0000		
2002	0.7997	0.8251	0.8104	0.8669	0.8214	0.8595	0.8944	0.9128	1.0000	
2001	0.8067	0.7849	0.7736	0.8701	0.8225	0.8391	0.8371	0.8339	0.9079	1.0000

PBT

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9386	1.0000								
2008	0.9228	0.9308	1.0000							
2007	0.9232	0.9272	0.9453	1.0000						
2006	0.9030	0.8726	0.9094	0.9526	1.0000					
2005	0.8620	0.8731	0.8789	0.9202	0.9466	1.0000				
2004	0.8636	0.8409	0.8562	0.8699	0.8756	0.9520	1.0000			
2003	0.8541	0.8192	0.8547	0.8798	0.8742	0.9178	0.9303	1.0000		
2002	0.8288	0.8324	0.8349	0.8763	0.8668	0.8789	0.8789	0.9161	1.0000	
2001	0.8336	0.7959	0.8021	0.8515	0.8034	0.8486	0.8264	0.8581	0.8812	1.0000

HE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9192	1.0000								
2008	0.9150	0.9211	1.0000							
2007	0.9127	0.9056	0.9418	1.0000						
2006	0.8791	0.8631	0.9142	0.9454	1.0000					
2005	0.8742	0.8670	0.8927	0.9192	0.9549	1.0000				
2004	0.8683	0.8390	0.8791	0.8980	0.9265	0.9574	1.0000			
2003	0.8345	0.8521	0.8417	0.8941	0.9200	0.9265	0.9532	1.0000		
2002	0.8327	0.7971	0.8315	0.8718	0.9037	0.8848	0.9153	0.9525	1.0000	
2001	0.8238	0.8061	0.8156	0.8346	0.8646	0.8482	0.8773	0.9173	0.9313	1.0000

TA

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9896	1.0000								
2008	0.9586	0.9652	1.0000							
2007	0.9527	0.9336	0.9516	1.0000						
2006	0.9223	0.8892	0.9140	0.9677	1.0000					
2005	0.9113	0.8759	0.9012	0.9505	0.9820	1.0000				
2004	0.9017	0.8681	0.8878	0.9406	0.9695	0.9814	1.0000			
2003	0.9109	0.9195	0.9285	0.9418	0.9589	0.9678	0.9811	1.0000		
2002	0.8865	0.8464	0.8660	0.9116	0.9350	0.9394	0.9484	0.9730	1.0000	
2001	0.8765	0.8341	0.8500	0.8998	0.9157	0.9112	0.9181	0.9467	0.9802	1.0000

IC

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9880	1.0000								
2008	0.9501	0.9547	1.0000							
2007	0.9448	0.9460	0.9480	1.0000						
2006	0.9042	0.9005	0.9042	0.9668	1.0000					
2005	0.9085	0.9066	0.9005	0.9551	0.9775	1.0000				
2004	0.8938	0.8980	0.8762	0.9402	0.9597	0.9759	1.0000			
2003	0.8969	0.9094	0.9106	0.9296	0.9462	0.9588	0.9768	1.0000		
2002	0.8819	0.8788	0.8529	0.9083	0.9282	0.9277	0.9320	0.9662	1.0000	
2001	0.8688	0.8645	0.8360	0.8912	0.9043	0.8986	0.8921	0.9360	0.9783	1.0000

BVE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9543	1.0000								
2008	0.9478	0.9654	1.0000							
2007	0.9240	0.9233	0.9327	1.0000						
2006	0.9123	0.9192	0.8969	0.9553	1.0000					
2005	0.9024	0.9045	0.9022	0.9376	0.9675	1.0000				
2004	0.8857	0.8776	0.8794	0.9046	0.9511	0.9638	1.0000			
2003	0.8665	0.8639	0.8473	0.8915	0.9115	0.9317	0.9504	1.0000		
2002	0.8521	0.8564	0.8388	0.8796	0.8982	0.9079	0.9150	0.9699	1.0000	
2001	0.8485	0.8538	0.8318	0.8771	0.8858	0.8931	0.9018	0.9452	0.9687	1.0000

R

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9794	1.0000								
2008	0.9392	0.9605	1.0000							
2007	0.9438	0.9684	0.9768	1.0000						
2006	0.9161	0.9458	0.9501	0.9684	1.0000					
2005	0.8956	0.9210	0.9178	0.9596	0.9809	1.0000				
2004	0.9013	0.9070	0.8974	0.9442	0.9431	0.9698	1.0000			
2003	0.8973	0.9144	0.8806	0.9448	0.9102	0.9698	0.9729	1.0000		
2002	0.8341	0.8538	0.7900	0.8839	0.8843	0.9579	0.9512	0.9850	1.0000	
2001	0.8611	0.8856	0.8089	0.8997	0.8519	0.9187	0.9125	0.9447	0.9365	1.0000

CgbO

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9395	1.0000								
2008	0.9166	0.9224	1.0000							
2007	0.8998	0.9044	0.9390	1.0000						
2006	0.8757	0.8674	0.9340	0.9278	1.0000					
2005	0.8886	0.8967	0.8983	0.9197	0.9429	1.0000				
2004	0.9161	0.8744	0.8984	0.9195	0.9454	0.9565	1.0000			
2003	0.8702	0.8540	0.8446	0.8940	0.9190	0.9260	0.9387	1.0000		
2002	0.8199	0.8164	0.8132	0.8409	0.8406	0.8956	0.9206	0.9255	1.0000	
2001	0.8537	0.8011	0.8473	0.8481	0.8490	0.8699	0.8819	0.8966	0.9050	1.0000

NCIfOA

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.8947	1.0000								
2008	0.8606	0.8545	1.0000							
2007	0.8847	0.8839	0.8815	1.0000						
2006	0.8572	0.8532	0.8673	0.9007	1.0000					
2005	0.8784	0.8502	0.8581	0.8799	0.8986	1.0000				
2004	0.8541	0.8354	0.7926	0.8358	0.8759	0.8927	1.0000			
2003	0.8623	0.8526	0.7972	0.8615	0.8893	0.8950	0.9119	1.0000		
2002	0.8499	0.8345	0.7768	0.8554	0.8062	0.8415	0.8724	0.9245	1.0000	
2001	0.8245	0.7409	0.7899	0.8688	0.8244	0.8191	0.8651	0.8861	0.8592	1.0000

NCIfIA

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.7865	1.0000								
2008	0.8011	0.8251	1.0000							
2007	0.7079	0.7450	0.8148	1.0000						
2006	0.7289	0.7419	0.8104	0.8467	1.0000					
2005	0.8324	0.8303	0.8194	0.7851	0.8469	1.0000				
2004	0.7196	0.6542	0.6466	0.6840	0.8001	0.7339	1.0000			
2003	0.7219	0.7210	0.7454	0.8515	0.8193	0.7616	0.7758	1.0000		
2002	0.7311	0.8192	0.8074	0.7509	0.7898	0.7292	0.7512	0.8084	1.0000	
2001	0.6154	0.5826	0.7913	0.7060	0.8094	0.7373	0.7259	0.7341	0.7046	1.0000

OD

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.9165	1.0000								
2008	0.8753	0.8752	1.0000							
2007	0.8620	0.8760	0.9461	1.0000						
2006	0.8304	0.7708	0.8652	0.9240	1.0000					
2005	0.7834	0.7326	0.8406	0.8918	0.9390	1.0000				
2004	0.7751	0.7481	0.8318	0.8768	0.8891	0.9023	1.0000			
2003	0.7742	0.7495	0.8036	0.8468	0.8704	0.8688	0.8899	1.0000		
2002	0.7174	0.7117	0.7749	0.8290	0.8559	0.8602	0.8723	0.9060	1.0000	
2001	0.7378	0.6861	0.7610	0.7913	0.8284	0.8165	0.8580	0.8329	0.8233	1.0000

FCFE

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.8215	1.0000								
2008	0.7817	0.7725	1.0000							
2007	0.7573	0.8436	0.8204	1.0000						
2006	0.7879	0.8268	0.6953	0.8163	1.0000					
2005	0.8474	0.8139	0.7404	0.7579	0.8294	1.0000				
2004	0.8227	0.7537	0.7494	0.7695	0.8065	0.8282	1.0000			
2003	0.8173	0.8165	0.6734	0.7757	0.8302	0.8389	0.8477	1.0000		
2002	0.7254	0.7272	0.7103	0.7657	0.7771	0.7664	0.7902	0.8472	1.0000	
2001	0.7582	0.7021	0.7191	0.7156	0.8494	0.8034	0.7876	0.7996	0.7690	1.0000

FCFF

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2010	1.0000									
2009	0.8497	1.0000								
2008	0.8303	0.8592	1.0000							
2007	0.8248	0.8616	0.8937	1.0000						
2006	0.8254	0.8297	0.8466	0.8592	1.0000					
2005	0.8553	0.8273	0.8515	0.8488	0.8844	1.0000				
2004	0.8544	0.7836	0.8051	0.8167	0.8237	0.8541	1.0000			
2003	0.8532	0.8698	0.7840	0.8447	0.8563	0.8784	0.8926	1.0000		
2002	0.7882	0.7880	0.7500	0.8157	0.8108	0.8691	0.8591	0.9216	1.0000	
2001	0.7920	0.7187	0.7757	0.8387	0.8574	0.8564	0.7700	0.8365	0.8544	1.0000