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The valuation performance of mathematically-optimised, equity-based composite multiples

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Abstract

Purpose – This paper aims to examine the valuation precision of composite models in each of six key industries in South Africa. The objective is to ascertain whether equity-based composite multiples models produce more accurate equity valuations than optimal equity-based, single-factor multiples models.

Design/methodology/approach – This study applied principal component regression and various mathematical optimisation methods to test the valuation precision of equity-based composite multiples models *vis-à-vis* equity-based, single-factor multiples models.

Findings – The findings confirmed that equity-based composite multiples models consistently produced valuations that were substantially more accurate than those of single-factor multiples models for the period between 2001 and 2010. The research results indicated that composite models produced up to 67 per cent more accurate valuations than single-factor multiples models for the period between 2001 and 2010, which represents a substantial gain in valuation precision.

Research implications – The evidence, therefore, suggests that equity-based composite modelling may offer substantial gains in valuation precision over single-factor multiples modelling.

Practical implications – In light of the fact that analysts' reports typically contain various different multiples, it seems prudent to consider the inclusion of composite models as a more accurate alternative.

Originality/value – This study adds to the existing body of knowledge on the multiples-based approach to equity valuations by presenting composite modelling as a more accurate alternative to the conventional single-factor, multiples-based modelling approach.

Keywords Emerging markets, Composite multiples, Equity multiples, Equity valuations, Valuation precision

Paper type Research paper

1. Introduction

This paper examines the valuation precision of composite models in each of six key industries in South Africa. The objective is to ascertain whether equity-based composite

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multiples models produce more accurate equity valuations than optimal equity-based, single-factor multiples models. The analysis will be conducted on an industry basis, as it is anticipated that different composite multiples models will be best suited to different industries (Abukari *et al.*, 2000; Barker, 1999; Fernández, 2001; Goedhart *et al.*, 2005; Liu *et al.*, 2002a; Nel, 2009a; 2009b, 2013b; Schreiner, 2007). Optimal equity-based composite multiples models will be constructed for each of the six South African industries, and their valuation precision will be compared to that of eight optimal equity-based, single-factor multiples models. The aim is to establish whether industry-specific, equity-based, composite multiples models offer higher degrees of valuation precision *vis-á-vis* industry-specific, equity-based, single-factor multiples models.

First, the proper composition of the composite models requires investigation. To this end, one has to determine the optimal weight allocations of each of the components of the composite models. This is achieved by using mathematical optimisation algorithms with the goal of minimising the sum of the absolute valuation errors (SAVE), the median valuation errors (MVE) and the sum of the squared valuation errors (SSVE). Second, the increase in valuation precision that composite multiples models may offer over single-factor multiples models is estimated. Third, the consistency of the results is assessed for the period 2001–2010.

Multiples are used extensively in practice, which is why analyst reports are typically inundated with various different single-factor multiples (Asquith *et al.*, 2005; Damodaran, 2009, 2006b; Efthimios *et al.*, 2004; Fernández, 2002; PricewaterhouseCoopers (PwC), 2015, 2012; Roosenboom, 2007). Therefore, there seems to be a case for compiling a composite of these single-factor multiples.

However, multi-factor modelling is not a new phenomenon in 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 (Nel *et al.*, 2014b). It is hoped that the findings from this paper will offer a new perspective for the composition of composite multiples models in emerging markets and in South Africa, in particular.

2. Literature review

Most of the existing international literature focuses on a composite of market price (P) to earnings per share (EPS) and book value of equity (BVE) per share. The use of a composite of P/EPS and P/BVE stems from the multitude of researchers who have attempted to investigate the nature of the relationship between accounting data and company value by focusing on these two multiples (Ohlson, 1995; Ohlson and Juettner-Nauroth, 2005; Penman, 1998). 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 precision of a two-factor composite model consisting of P/BVE and other earning-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 US-based companies for the period 1982-2004 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 precision 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 (trailing) and P/EPS (forecast), for companies in the USA for the period 1986-2004, and found that the composite models outperformed individual multiples.

Penman (1998) tested composite multiples for American companies based on EPS, book value and price data obtained from the Compustat database for the 25-year period from 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 precision.

Extracting data from the Compustat and Institutional Brokers Estimation System databases for the period 1981 to 1999, Yoo (2006) tested the valuation precision of a composite of earnings, book value, earnings before interest, tax, depreciation and amortisation (EBITDA) and revenue multiples compared to the respective individual multiples. The results indicated that the composite model offered an increase in valuation precision 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, among other limitations, to include cash flow–value driver-based multiples in the composite multiple or to distinguish between equity- and company-based multiples. Regrettably, the matching principle is often neglected by analysts, which could result in substantial mispricing of the equity of companies with leveraged capital structures (Nel, 2014f). 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 empirical testing, by means of linear modelling and/or non-linear weight allocations, of the valuation precision of composite models that combine information from various value driver categories, including cash flows. In addition, the focus of this study is on equity-based composites, in particular. 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 precision.

The evidence from the developed market literature, therefore, suggests that composite modelling produces more accurate valuations than single-factor 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, for the period 1993–2007. 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. 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 *et al.*, 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 analysts and academic researchers alike, i.e. they fail to distinguish between equity- and company-based valuations (Nel *et al.*, 2013b).

Regrettably, the limited scope of the study by Sehgal and Pandey prohibits a more detailed analysis. Consequently, this paper 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.

3. Empirical design

3.1 Data

The composite models constitute equity-based compilations of the eight equity-based, single-factor multiples models, as contained in Table I. The equity-based focus of this paper stems, first, from the objective of this study, which is to investigate the valuation precision of equity-based composite multiples models, in particular and, second, from the finance literature that suggests that equity-based multiples outperform company-based multiples in terms of valuation precision (Nel *et al.*, 2013b; Schreiner, 2007)[1].

The data items were extracted from the McGregor BFA database, one of the leading data houses in South Africa, for the period 2001-2010 (PwC, 2015). 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 (Damodaran, 2009, 2006a; Nel *et al.*, 2014e, 2013b; Schreiner, 2007). Although one may be tempted to incorporate company-based, single-factor multiples into the equity-based composite model, this will result in model inconsistencies, which may obscure the interpretation of the results. The number of observations varied for each equity-based multiple, depending on the specific industry in question. The population sizes per industry varied between 242 and 1,248 observations.

The focus in this paper is primarily on equity-based multiples and their behaviour in each of six key industries, namely basic materials, consumer goods, consumer services, financials, industrials and technology. As a result of data limitations – a common phenomenon in developing markets (Omran, 2003; Sehgal and Pandey, 2009) – a sector-based approach was not possible. Instead, an industry-based approach was adopted. Although ten industries are demarcated on the McGregor BFA database, insufficient data is

Value drivers			
Earnings	Assets	Dividends	Cash flow
MPV			
P			
PBT	BVE	OD	NCIfOA
PAT			NCIfIA
HE			FCFE

Notes: MPV – market price variable; P – market price; PBT – profit before tax; PAT – Profit after tax; HE – headline earnings; BVE – book value of equity; OD – ordinary dividends; NCIfOA – net cash inflow from operating activities; NCIfIA – net cash inflow from investment activities; FCFE – free cash flow to equity. Own elaboration

Table I.
Equity-based, single-factor multiples

available for four of these industries, namely healthcare, oil and gas, telecommunications and utilities. Consequently, these four industries are omitted from the analysis, and the focus is on the six key industries, for which sufficient data is available.

3.2 Model specification

Multiples-based equity valuations assume that the actual equity value (V_{it}^{e}) of a company (i) at a given point in time (t) is equal to the product of a multiple (λ_{t}^{e}) and a specific value driver (α_{it}) at that specific point in time, so that

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

Refer to Nel, Bruwer and Le Roux (2014a) for more details pertaining to single-factor multiples. In this paper, the market-based approach, as modelled in Equation (1), is adopted. To investigate the valuation precision of composite multiples models, Equation (1) is extended to accommodate composite modelling:

$$\hat{V}_{it}^{e} = \sum_{j=1}^{k} \beta_{jt} \cdot \hat{\lambda}_{jpt}^{e} \cdot \alpha_{jit} \tag{2}$$

where $\hat{V}_{it}^{e}$ is the predicted equity value of company 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 aim of the research is to establish the ability of valuations based on Equation (2) to approximate actual share values. Functions for the calculation of $\hat{V}_{it}^{e}$ and the statistical analysis thereof were developed in the R-package, an open source programming language that lends itself to statistical analysis and graphics (R Core Team, 2015). The optimal number (k) of single-factor multiples models that is catered for in each composite model will depend on the optimal weightings (β_{jt}), 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. A high level of multicollinearity was anticipated amongst the respective value drivers. Therefore, principal component analysis (PCA) was applied to transform the initial multi-variable data set into uncorrelated combinations (principal components) of the original independent variables, which nullified kappa readings (measure of multicollinearity) to insignificant numbers. All of the principal components were, therefore, independent of each other after transformation. However, there were assumption violations in our application pertaining to principal component regression (PCR), which constitutes a linear regression approach. Therefore, as a result of these violations, we adopted a direct constraint optimisation approach, aimed at optimising the median absolute valuation errors and not the sum (or mean) of the squared evaluation errors. The β-value refers to the corresponding weightings for each of the single-factor multiples, which will be determined by mathematical optimisation applications in the *R-package*. The assumptions regarding β are that $0 \leq \beta_{1t}, \beta_{2t}, \ldots, \beta_{kt}, \leq 1$ and $\sum_{j=1}^{k} \beta_{jt} = 1$.

The composite multiples models' predicted equity values will, therefore, encapsulate the weighted average of the predicted values of the respective single-factor multiples. Subtracting Equation (2) from the actual equity value (V_{it}^{e}) of a company (i) at a given point in time (t) produces the valuation error margin:

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

As the valuation error margin will be size-dependent, the standardised absolute deviation (ε_{it}) is expressed proportionally to the actual equity value, V^{e}_{it}; therefore:

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

The market-based approach that is adopted in this paper was introduced to the finance literature by Alford (1992) in a joint research effort between the Massachusetts Institute of Technology and corporate financiers from Ernst & Young. It has since been refined by various scholars (Berkman *et al.*, 2000; Cheng and McNamara, 2000; Dittmann and Weiner, 2005; Gilson *et al.*, 2000; Kaplan and Ruback, 1995; Liu *et al.*, 2007, 2002a; 2002b; Minjina, 2008; Nissim, 2011). From the literature review, it is evident that the 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 weightings were not restricted, i.e. when the single-factor multiples models were not allocated an equal weighting, the valuation precision of the composite multiples models increased *vis-á-vis* equally weighted composite multiples models. The objective of the resulting optimisation process in composite-based modelling is the minimisation of the valuation error, as per Equation (4).

Various methods were considered for determining the optimal weight allocations of the components of the composite models. Among the alternatives considered were R-based PCA, PCR and three mathematical optimisation applications, namely, *lpSolve, Rsolnp*, as well as *Quadprog*. Unfortunately, the nature of the data rendered some 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, *lpSolve, Rsolnp*, as well as *Quadprog*.

3.3 Mathematical optimisation

As the objective of the optimisation process is to determine the optimal weightings 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 use more than one optimisation method, namely, SAVE, MVE and SSVE. 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 first application, *lpSolve*, optimises the weight allocations based on the objective of minimising the SAVE. The *lp* function, which is an integer programming application in the *R-package lpSolve*, was used to apply the SAVE method. The objective of the *lp* function was to produce optimal weightings to be allocated to each of the single-factor multiples models included in the composite multiples models, to minimise the SAVE. To this end, the *R function SAVE* was written to effect the optimisation of the objective function [Equation (5)]:

$$\min_{\mathbf{a}} \sum_{i=1}^{n} \left(\frac{\left| y_i - \mathbf{m}_i' \mathbf{a} \right|}{y_i} \right)$$
$$\text{subject to} \quad \begin{cases} \sum_{j=1}^{p} a_j = 1 \\ a_j \geq 0 \, \mathit{for\ all}\, j \end{cases} \tag{5}$$

where y_i is the i^{th} actual equity value, while $\mathbf{m}_i'$ represents a vector of equity value estimates corresponding to y_i and **a** denotes the weight allocation to each single-factor multiple. The vector **a** is of size p – the number of single-factor multiples.

However, a key focus point in the international literature is the minimisation of the MVE (Schreiner, 2007). Consequently, an *R function*, namely, *MinMed3*, which focuses on the minimisation of the MVE, was written to implement the following:

$$\text{Let}\, d_i = \left(\frac{\left| y_i - \mathbf{m}_i' \mathbf{a} \right|}{y_i} \right) \qquad \mathit{for}\ i = 1,\ 2,\ \ldots,\ n \tag{6}$$

The median of the values (d_i), as defined in function [Equation (6)], is minimised by *MinMed3*.

The output of *MinMed3* contains the optimal weightings of the various single-factor multiples models contained in the composite multiples models. The MVE approach was affected via the *solnp* function, a non-linear optimisation function based on the Lagrange method, in the R-package *Rsolnp*.

The third application, namely, Q*uadprog*, 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. The second application, *Rsolnp*, which optimises the weight allocations based on the objective of minimising the MVE, 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 those of studies which applied median-based valuation errors in the US and European markets.

As 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.

3.4 Local minimums when optimising beta

The risk with local minimums is that the β-values offered by the optimisation applications may not be optimal, i.e. they could differ substantially from global minimums (Le Roux *et al.*, 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 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.

Table II, 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 optimal output of *SAVE* becomes the starting parameter vectors in

	Composites 2010							
	Value drivers							
	Earnings			Assets	Dividends	Cash flows		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Basic materials								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	0.0131	–	0.4213	0.1617	–	0.4039	–	–
Optimal MVE-based weightings	0.0026	–	0.4771	–	0.5203	–	–	–
Consumer goods								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	–	–	0.7674	0.0644	–	0.1683	–	–
Optimal MVE-based weightings	–	–	0.8181	0.0929	0.0890	–	–	–
Consumer services								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	–	–	1.0000	–	–	–	–	–
Optimal MVE-based weightings	–	–	1.0000	–	–	–	–	–
Financials								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	–	0.1593	0.8407	–	–	–	–	–
Optimal MVE-based weightings	–	0.0206	0.9794	–	–	–	–	–
Industrials								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	–	–	0.2025	0.5047	0.0678	–	0.1991	0.0260
Optimal MVE-based weightings	–	–	0.0057	0.6361	–	0.2679	0.0108	0.0795
Technology								
Initial SAVE-based weightings	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Optimal SAVE-based weightings	–	–	0.6583	–	–	0.3417	–	–
Optimal MVE-based weightings	–	–	0.9675	–	0.0325	–	–	–

Own elaboration

Table II.
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

MinMed3. As is evident from Table II, the output from *SAVE* is optimised further via *MinMed3* to eventually reach the optimal MVE-based weightings. A substantial improvement in the valuation precision 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 (Le Roux *et al.*, 2014d).

Although it is impossible to determine conclusively whether the final solution constitutes the global minimum, the aim of this study is not to establish whether the valuation error is at the global minimum. The objective is merely to establish whether 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.

4. Empirical results and discussion

The empirical analysis initially focuses on the correlation matrices of market capitalisation (MCap) and all eight equity-based value drivers for the period between 2001 and 2010. The focus then shifts to the correlation matrices of the eight equity-based value drivers over the market as a whole, as well as within the six key industries, including a discussion of the occurrence and mitigation of multicollinearity. This is followed by a framework for 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 I, to determine the magnitude of the increase in valuation precision, if any. Lastly, the consistency of the results is investigated for the 10-year period between 2001 and 2010 and compared to evidence from the developed market literature and the only other emerging market study of this kind.

4.1 Consistency of the market price variable and value drivers over time

An analysis of the observed relationships between MCaps for the period 2001–2010 is contained in Table III. All the MCaps were positively correlated, and very strongly so, with correlation coefficients ranging between 0.8472 and 0.9813. Therefore, a high MCap in any particular year for the period 2001-2010 is likely to be accompanied by a high MCap in the other nine years as well.

A similar conclusion can be drawn from the value drivers contained in Table III, i.e. all the observed relationships were positive, and, with the exception of OD, net cash inflow from investment activities (NCIfIA) and free cash flow to equity (FCFE), these relationships were very strong, with correlation coefficients ranging between 0.7409 and 0.9699. 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 pair-wise 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 – the only reading below 0.70 – but is still relatively high. The NCIfIA-based correlation matrix, however, contains five correlation coefficients below 0.70, ranging between 0.5826 and 0.6840. They are the pair-wise 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 MCap based on these value drivers in any particular year for the period 2001 to 2010 is likely to

Table III. Correlation matrices of MCap and corresponding value drivers for the period 2001-2010

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
MCap										
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
PBT										
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
PAT										
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
HE										
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

(*continued*)

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
BVE										
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	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
NCIfOA										
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	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

(*continued*)

Table III.

	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
FCFE										
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

Notes: 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 as it diminished the impact of these outliers. Own elaboration

Table III.

have produced a high estimate of MCap 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.

4.2 Multicollinearity

Table IV contains the pair-wise Pearson correlations of all eight value drivers of the market as a whole for 2010. All eight value drivers exhibit positive and very strong relationships. Overall, the correlation coefficients range between 0.6220 and 0.9912, which may suggest that not all the value drivers share the same information content.

Two exceptions are noted, namely, the pairwise combinations of ordinary dividends (OD) and net cash inflow from operating activities (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 also across all the value drivers, i.e. including those that were extracted from other types of financial statements.

From the evidence presented by Nel *et al.* (2014e, 2013d), one would be inclined to argue that the construction of a composite multiples model should incorporate headline earnings (HE) as an independent variable. From the correlation coefficient matrix in Table IV, it

	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
PBT	1.0000							
PAT	0.9912	1.0000						
HE	0.9404	0.9380	1.0000					
BVE	0.8007	0.8292	0.8173	1.0000				
OD	0.8180	0.8237	0.7952	0.7330	1.0000			
NCIfOA	0.8734	0.8669	0.8467	0.8021	0.6919	1.0000		
NCIfIA	0.7987	0.7876	0.7525	0.7641	0.6220	0.8802	1.0000	
FCFE	0.8567	0.8469	0.8275	0.7924	0.7311	0.8928	0.9102	1.0000

Own elaboration

Table IV.
Correlation matrix for the entire market for 2010

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 comprehensive income, in particular, exhibit very high correlation coefficients – in the vicinity of 0.94 or higher. Similarly, value drivers that were extracted from the cash flow statement share considerable information content, which is evident from their respective correlation coefficients of around 0.90 or higher. This suggests a high likelihood of encountering a fair amount of multicollinearity when using regression analysis to the data.

The correlation matrices discussed thus far were based on the market as a whole, while the focus of this paper is on the construction of industry-specific composite multiples models. Consequently, it is equally important to compare the correlation coefficients of the equity-based value drivers on an industry basis as this forms the basis of the composite modelling. Table V contains these matrices for 2010.

The correlation coefficients contained in Table V 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 in this paper is based. Although the majority of the pair-wise 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 earning-based value drivers, indicating pairwise correlation coefficients between 0.5216 and 0.5875. Similarly, OD is poorly correlated with all the cash-flow-based value drivers, indicating pair-wise correlation coefficients of between 0.2182 and 0.6325. OD is particularly poorly correlated with NCIfIA, 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 by 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.

4.3 Composite model framework

To compile the composite multiples models, it was necessary to obtain the optimal weightings for each of the components to be included in each model. All eight equity-based single-factor multiples contained in Table I, 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 as 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 a company's profitability, it does not represent cash in the bank for shareholders, i.e. profit after tax (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 V. Correlation matrices for each of the six key industries for 2010

	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Basic materials								
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	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 goods								
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	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
Industrials								
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

(*continued*)

	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Technology								
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

Own elaboration

Table V.

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 VI.

The following can be gleaned from the composite models: First, 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.

Second, the evidence suggests that there is no one-size-fits-all composite framework 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 just two.

Third, 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 precision of the composite models.

Fourth, note how earning-based single-factor multiples models dominate the composition of the composite multiples models over all six industries. On average, earning-based value drivers, as a category, comprise between 40.90 and 89.68 per cent of the composite models, which confirms the superior valuation performance of earning-based multiples evident in the literature (Nel *et al.*, 2014e, 2013d). Earning-based multiples carried a particularly heavy weighting in the consumer services and technology industries, comprising, on average, 89.68 and 78.05 per cent of the composite models respectively.

On an individual value driver basis, on average, the weighting assigned to HE is between 27.29 and 78.55 per cent, 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 per cent), technology (62.67 per cent) and industrials (56.62 per cent). Profit before tax (PBT) managed to secure weightings of, on average, between 1.99 and 14.27 per cent over all the industries, with the exception of the consumer services industry, where it failed to secure a weighting. Similarly, PAT carried an average weighting of between 0.87 and 19.96 per cent over all six industries.

Table VI. Single-factor multiples models and their weightings, as included in the composite multiples models of six key South African industries for the period 2001-2010

	Value drivers							
	Earnings			Assets	Dividends	Cash flows		
	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE
Basic materials								
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								
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	0.0131	–	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
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

(*continued*)

					Value drivers			
		Earnings		Assets	Dividends		Cash flows	
	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
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
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

Notes: Note that there are years in which no weightings are allocated to any of the single-factor multiples, for example, 2004 in the consumer goods industry. This stems from insufficient data availability. Own elaboration

Table VI.

These findings concur with earlier evidence in the literature regarding the valuation performance of the P/HE, P/PBT and P/PAT single-factor multiples (Nel *et al.*, 2014e).

Fifth, note the cash-flow-based value driver category's unexpected contribution to the composition of the composite models. As a value driver category, cash flows generally produce the least accurate valuations, even less so than revenue (Nel *et al.*, 2014e; 2013d). 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 per cent and between 1.11 and 14.95 per cent 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 to 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 five per cent of the composite models across all six industries. The latter concurs with the relatively poor valuation performance of P/FCFE as a single-factor multiple (Nel *et al.*, 2014e, 2013d).

Sixth, 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 similar. The contribution of BVE to the composite models varied between 0.84 and 25.84 per cent and was particularly prevalent in the basic materials and financials industries, where it occupied, on average, 25.84 and 20.03 per cent component shares, respectively. However, the contribution of BVE in the consumer services (0.84 per cent) and technology (3.05 per cent) 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 (Penman, 1998; Schreiner, 2007; Yoo, 2006).

Seventh, 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 per cent. OD's weightings in the consumer services (3.65 per cent) and technology (2.43 per cent) industries were insubstantial. OD carried its highest weighting in the financials (14.90 per cent), industrials (14.88 per cent) and consumer goods (14.55 per cent) industries.

These results suggest that composite multiples models offer superior explanatory power as compared to single-factor multiples models[2]. The question, however, is whether the increase in valuation precision that is offered by composite modelling, as compared to the more traditional single-factor modelling, is substantial.

4.4 Comparison between composite models and traditional models

The relative valuation performance of the composite multiples models and single-factor multiples models for the entire period from 2001 to 2010 is displayed in Table VII. 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 precision of equity-based multiples for the period 2001-2010 is also summarised in Table VII.

Table VII. The relative valuation performance of composite multiples models and single-factor multiples models for the period 2001-2010

							Value drivers				Average over
				Earnings		Assets	Dividends		Cash flows		all six
Years	IMP (%)	Composite	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	industries (%)
Basic materials											
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											
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	1.92445	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										

(*continued*)

Table VII.

						Value drivers					
			Earnings			Assets	Dividends		Cash flows		Average over all six
Years	IMP (%)	Composite	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	industries (%)
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										
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										

(*continued*)

Table VII.

							Value drivers				Average over
				Earnings		Assets	Dividends		Cash flows		all six
Years	IMP (%)	Composite	PBT	PAT	HE	BVE	OD	NCIfOA	NCIfIA	FCFE	industries (%)
Industrials											
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										
Industrials											
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										

Own elaboration

Note that the potential percentage increase in valuation precision (IMP) in Table VII indicates 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. See Nel *et al.* (2014e) for a detailed discussion of the construction of optimal single-factor multiples. 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 VII, the results indicate that on average, there are substantial gains to be secured by using 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 VII. The range of average annual IMPs over all six industries for each of the 10 years lies between 20.21 and 44.59 per cent, 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 10-year period, with an IMP range, on average, of between 10.12 and 44.11 per cent. With the exception of the consumer services industry, which secured precision gains of 10.12 per cent, all the industries indicate gains in excess of 25 per cent, on average.

Aside from the *lp* function in the R-package *lpSolve*, the *solnp* function (in the R-package *Rsolnp*), which is particularly adept at handling non-linear optimisations, was also used to determine the optimal weightings. Although not shown here, 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 per cent over the 10-year period[3]. On a per industry basis over the 10-year period, the IMPs, on average, ranged between 14.39 and 72.64 per cent. All the industries indicated substantial precision gains of 30 per cent or higher, on average, with the exception of the consumer services industry, which indicated an average gain in valuation precision of 14.39 per cent.

Although the data contained in Table VII reflects the magnitude of the increase in valuation precision that composite modelling may offer over single-factor modelling, the multi-dimensional nature of the data obscures a comprehensive grasp of the relative valuation performance of composite modelling over time. This is an important consideration for the way in which composite multiples models should be applied in practice. Because 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 *et al.*, 2011). However, the use of PCA biplots accommodates higher-dimensional data by approximating it in lower, usually two-dimensional space, thereby enabling the visualisation of multi-dimensional data.

4.5 Consistency of the valuation performance of composite models over time

The superior valuation performance of composite multiples models relative to single-factor multiples models can be illustrated more effectively with the help of PCA biplots. Figure 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 for 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 for the period from 2001 to 2010. For a more detailed discussion on the use of biplots, see Gower *et al.* (2011).

Note that the axes are colour-coded. The ten pink axes reflect the fact that composite multiples models produced more accurate valuations than single-factor multiples models for all ten years between 2001 and 2010. The quality of display reading of the PCA biplot in Figure 1 is 75.09 per

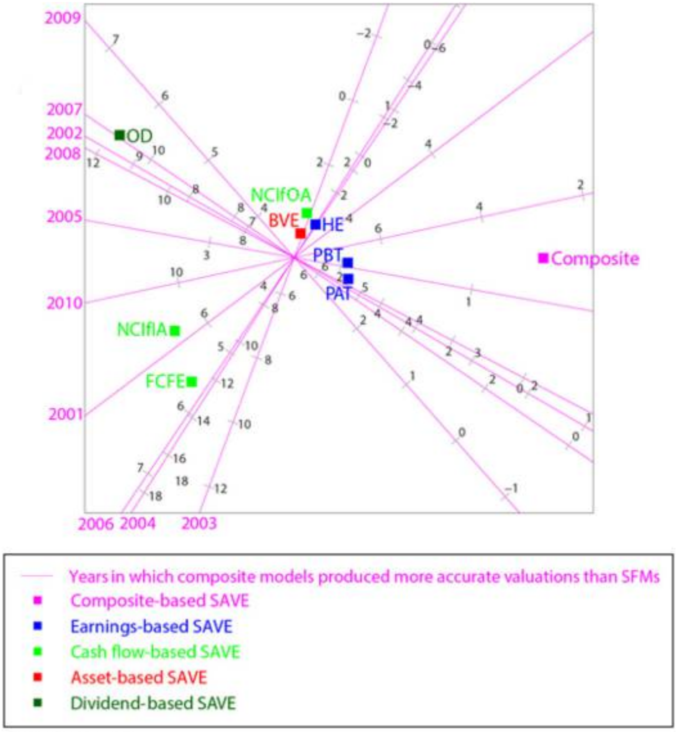

Figure 1.
PCA biplot of the valuation performance of the composite multiples models and the equity-based single-factor multiples models in the basic materials industry for the period 2001 to 2010

Own elaboration

cent and the predictivity readings fall 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.

In summary, the evidence from the South African market suggests that a composite modelling approach to equity valuations outperforms the traditional single-factor modelling approach. How do these results compare with the results from other emerging markets and developed markets?

4.6 International comparison

Unfortunately, composite-related studies are limited, both in number and 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. Those studies that do offer a comparative perspective on composite modelling, both concur with, and contradict, the findings from this paper.

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 per cent more accurate valuations than single-factor multiples models in the USA and 15.32 per cent 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

Section 4.4, it is evident that the magnitude of the improvement in valuation precision is more substantial in South Africa's case. Unfortunately, a more detailed comparison is not possible as none of Schreiner's selected industries correspond with any of the six key industries in the South African study.

However, the research results from this paper are in stark contrast with the results produced by Sehgal and Pandey (2010), who found conflicting evidence in South Africa's case. On the basis of the root mean squared errors method, they found that two-factor composite multiples models failed to outperform optimal single-factor multiples models. Then, on the basis of Theil inequality coefficients, they found an insubstantial improvement in valuation precision of 4.17 per cent. Equally insubstantial and inconsistent results were found for the other emerging markets.

5. Conclusion

The aim of this paper was to determine whether industry-specific, equity-based, composite multiples models offer higher degrees of valuation precision compared to industry-specific, equity-based, single-factor multiples models. The findings confirmed that equity-based composite multiples models produced valuations that were substantially more accurate than those of single-factor multiples models.

The study focused on equity-based multiples, in particular, and the results were tested for the period between 2001 and 2010. On the basis of the SAVE method – the primary optimisation method that was applied in this study – composite models, on annual average, produced between 20.21 and 44.59 per cent more accurate valuations than single-factor multiples models for the period 2001–2010 did. Although this already presents a substantial IMP range, the results obtained from the MVE method indicated an even higher average annual IMP range of between 12.65 and 66.98 per cent. However, these results were not equally consistent over all six key industries. The composite multiples models failed to offer higher degrees of valuation precision 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 within the context of composite modelling. The market- and industry-based research findings obtained from the finance literature suggest that dividends produce 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 the finance literature suggests generally produces poor valuations in terms of valuation precision, managed to secure a higher weighting than the asset- and dividend-based value driver categories, on average.

As was gleaned from the finance literature, earning-based multiples contributed substantially to the valuation precision of the composite multiples models. Accordingly, earning-based multiples did, indeed, dominate the composition of the composite multiples models. Earning-based multiples occupied, on average, between 40.90 and 89.68 per cent 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 per cent, on average. These results concur with the valuation performance of earning-based multiples, and HE as a single-factor multiple, in particular, in the finance literature.

The evidence, therefore, suggests that equity-based composite modelling may offer substantial gains in valuation precision over equity-based, single-factor multiples modelling. These gains are, however, industry-specific and a *carte blanche* application thereof is ill advised. Therefore, as analysts' reports typically contain various single-factor 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 this study differ from those 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.

The focus of this study was on equity-based modelling in particular. Although one may be inclined to consider company-based variables for inclusion in composite models, these models should be constructed in an internally consistent manner. Failure to do so may result in conceptually flawed models, which may obscure the interpretation of the results. Although it was not the focus of this study, a separate study, focused on company-based composite modelling, may produce interesting results.

Notes

1. Note that incorporating company-based, single-factor multiples into the equity-based composite model will result in model inconsistencies, which may obscure the interpretation of the results.
2. The data were also subjected to PCA on a per industry basis, following which PCR analysis was applied to the resulting two or three principal components, with similar results. 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 per cent 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.
3. The SSVE method was also 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, these results are not shown here.

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