Intellectual capital and firm performance among JSE-listed firms

Kevin Schutz

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DECLARATION

I, Kevin Schutz, declare that this research article is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Kevin Schutz

Signed at ……………Bedfordview………………………………………

On the …………28……………….. day of ………October…… 2018..

DEDICATION

This research project is dedicated to my wonderful and loving fiancé, Angelique Andrade. Without her encouragement, I would never have started the MBA, and without her support, I would never have finished it.

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- 1 excel file containing the complete panel data set
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ABSTRACT

With the burgeoning of the Fourth Industrial Revolution, there is an ever greater reliance on knowledge work as it becomes the source of company productivity. With this in mind, capturing the impact of the value added by employees through intellectual capital has growing importance as a potential means of evaluating firm performance. The study seeks to aid in the analysis of financial and market performance of firms using an intellectual capital metric known as the Value-added Intellectual Coefficient (VAIC) (Pulic, 2000). Financial performance data including return on assets, revenue growth, headline earnings per share and market performance, as defined by market-to-book ratio and total share return, were gathered on 43 qualifying JSE-listed firms for the period from 2001-2017.

Panel regressions were performed for each of the considered performance metrics for all firms and the entire period utilising both the complete VAIC model as well as its individual constituents, Intellectual Capital Efficiency (ICE) and Capital Employed Efficiency (CEE). For a thorough analysis, other significant control variables for firm specific factors were included such as the debt ratio, market capitalisation size, industry type and return on equity.

No significant associations resulted from the empirical analysis with regards to the role played by intellectual capital as defined by VAIC or its constituents for any of the financial or market performance metrics in a South African context.

Whilst the importance of the role of intellectual capital is intuitively undeniable, greater work is yet required to capture and quantify its impact to allow for a relation to, and thus more insightful evaluation of, firm performance through common financial and market measurements.

Keywords: Intellectual Capital; VAIC; Firm performance; South Africa

Chapter 1. Introduction

1.1 Purpose of the Study

The purpose of this study was to investigate the impact of intellectual capital on financial and market performance amongst individual firms listed on the Johannesburg Stock Exchange (JSE).

1.2 Context of the Study

As business moves deeper into the knowledge worker era, Intellectual Capital (IC) has become increasingly important, a resource as vital to a successful business as physical and financial capital.

This change is evidenced by labour trends in the USA, where in the 1980's, the labour force could be broken down into approximately three categories, routine manual work, routine office work, and knowledge work, or "non-routine cognitive work" (Zumbrun, 2016). Where the two routine classes of work have remained at approximately 30 million each in terms of labour force size, knowledge work has more than doubled to over 60 million (Zumbrun, 2016).

Similar growth in knowledge work has been noted in Europe. The European Commission (EC) states that currently over 90% of professional occupations require some degree of digital competency (European Commission, 2014a). Within Europe, work within the Information and Communications Technology (ICT) field is in such demand that there is a projected shortfall of 825 thousand skilled employees in this field by 2020 (European Political Strategy Centre, 2016). The EC deems development of knowledge work so important, in the form of digital skills, that it has set up the Digital Skills and Jobs Coalition, to actively encourage the development of digital skills within Europe. This is irrespective of industry or profession and highlights that at least some degree of knowledge work proficiency is becoming a pre-requisite across the board (European Commission, 2014b). The growing demand for knowledge work proficiency is only set to be further fuelled by the Fourth Industrial Revolution, as technology becomes even more engrained in our day to day lives. The European Skills Agenda to allow European workers to not only keep pace with developments but also to allow European workers and industries to actively harness the potential of it to foster greater productivity and growth (European Commission, 2018).

This digital dependency is only set to increase. The rapidity with which knowledge and skills must develop to keep pace with and match the requirements of the likes of the Fourth Industrial Revolution continues to escalate. A recent report by the World Economic Forum on the future of jobs stated that a popular estimation is that as of 2016, 65% of new primary school pupils will eventually work in fields that don’t yet even exist (World Economic Forum, 2016).

As a specific industry example, so vital is knowledge work in modern manufacturing plants, that the International Automotive Task Force (IATF), in its latest manufacturing standard, IATF 16949:2016, it has made it mandatory for suppliers to automotive Original Equipment Manufacturers (OEMs) to have specific knowledge management practices within the company. This is to ensure that employee knowledge is actively quantified, developed and distributed to supporting employees to alleviate potential risks to manufacturing quality and delivery that may arise from the loss of this knowledge (International Automotive Task Force, 2016). This development in the knowledge work field has enabled global productivity to experience steady growth into the technology and information age in-spite of challenges such as the 2009 financial crisis. This trend is indicated in the following figure (The World Bank, 2018b):

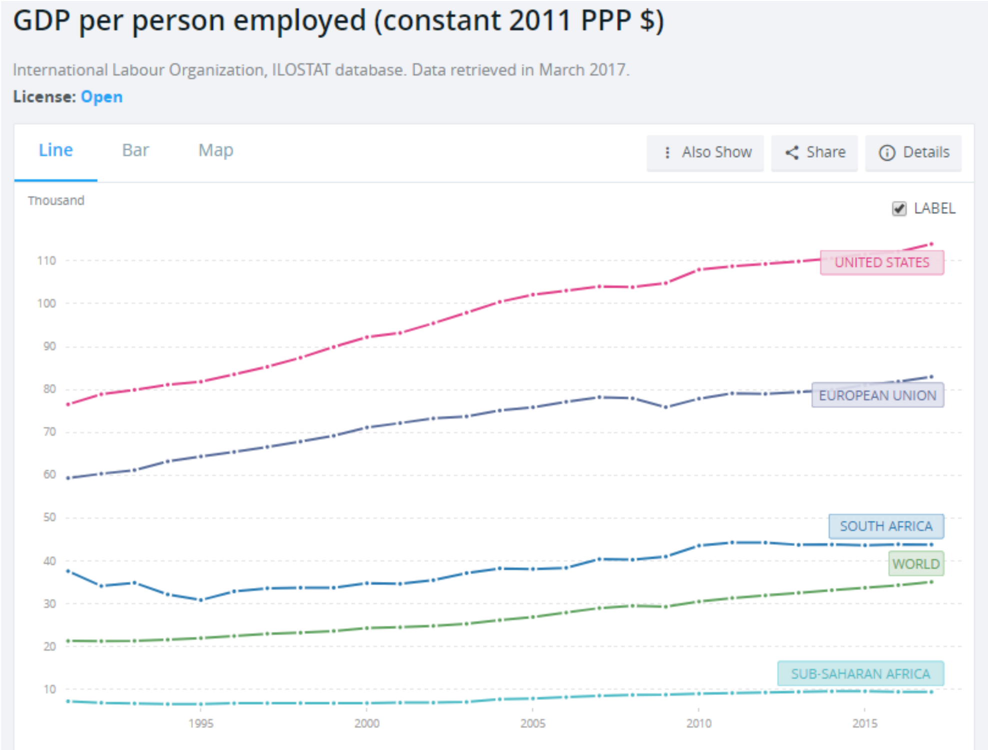

Figure 1: Labour Productivity as measured by GDP per person employed[1]

These growth trends indicate the decisive role that intellectual capital, in the form of knowledge work performed by employees, can play in ensuring productivity improvements and thus, by extension, the importance of intellectual capital within individual firms.

From the above figure it is apparent that the productivity of African states is underperforming relative to developed regions such as the United States of America (USA) and the European Union (EU). This indicates that there is significant opportunity for African countries to increase their productivity, with intellectual capital representing one possible means of doing so.

South Africa remains the leader in Africa from a productivity perspective. This has been enabled through continued growth in local labour productivity post-1994 as displayed in the figure below (South African Reserve Bank, 2018):

[1] (The World Bank, 2018b)

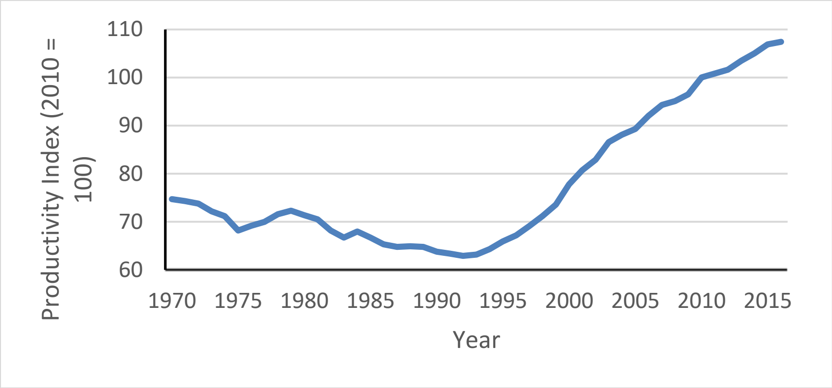

Figure 2: Labour productivity, South Africa: 1970 – 2016[2]

These productivity strides have occurred despite the overall skills level within the South African workforce not altering dramatically since the inception of democracy. There is still a heavy reliance on semi-skilled labour and only relatively minor up- and down-swings in the percentage of skilled and low-skilled workers respectively. Stats SA found in 2014 that overall structure of the workforce had moved very little between 1994-2014, as indicated by the following table(Stats SA, 2014):

Table 1: Breakdown of the South African workforce by skill level[3]

Skill Level	1994	2014
	% Breakdown of workforce	
Skilled	21%	25%
Semi-skilled	47%	46%
Low-skilled	32%	29%
Total	**100%**	**100%**

This is in contrast to the changes noted within the American labour market above (Zumbrun, 2016) and is likely a result of the fact that South Africa remains highly reliant on manual labour within many primary and secondary industries. This trend is likely to continue, with less than a third of South African companies consulted considering investment in automation according to a 2015 Grant Thornton International Business Report (Jonker, 2015).

[2] (South African Reserve Bank, 2018)
[3] (Stats SA, 2014)

This highlights the fact that there is still substantial room for improvement in terms of the effective productivity of the South African labour force on a macro-scale, meaning it is an area worth exploring. The ability to develop and maximise the productivity of employees at all skill levels could be a differentiator that will indicate those companies who may yield stability or growth locally.

One of the challenges in evaluating the link between productivity and economic growth is utilising a suitable value or metric that can represent employees at a firm level. One possible means of doing this is through the use of intellectual capital. Intellectual capital is often defined as comprising of human capital and structural capital (OECD (1999) as cited in Petty and Guthrie (2000)). Human capital refers to human resources or employees and the abilities or attributes they possess, such as knowledge, talent and experience. Structural capital consists of the intangible infrastructure of the company such as its intellectual property, business culture and processes, supply chain and management philosophy (Cronje & Moolman, 2013). Another component of intellectual capital is that of Relational Capital (RC), which is defined as the network of relationships that a firm has with the outside world, encompassing items such as its customers and stakeholders, that can enhance or detract from firm performance (Meles, Porzio, Sampagnaro, & Verdoliva, 2016). The application of these intangible resources is in effect what drives value-adding activities of companies, and the efficiency of this application is what drives value-creation or value-destruction within companies (Pulic, 2004). Thus intellectual capital can potentially be the source of improved productivity, particularly within the knowledge worker era.

One of the difficulties with establishing the efficiency with which intellectual capital is employed lies in the nature of how intellectual capital is measured and disclosed. Intellectual capital is often expressed in annual reports through written accounts of policies or approaches. For example, in South Africa specifically, this could entail disclosing information on employee health and safety or training and development policies (Wagiciengo & Belal, 2012). As a result of this the real value of these intangible assets is not quantified and thus is not reported on in financial results (Cronje & Moolman, 2013). In fact some intellectual capital components cannot be recognised or measured as assets from an accounting perspective due to the risk associated with the valuation of these assets as there is the risk of subjectivity (IASB (2011) as cited in Cronje and Moolman (2013)). Hence, accurately measuring the effects of intellectual capital quantitatively poses a challenge due to its very nature, and this difficulty is enhanced when consideration of the efficiency of the intellectual capital is the objective.

In order for a holistic evaluation of the efficiency of intellectual capital at creating value, the efficiency with which capital is employed will also be worthy of consideration, as it is the culmination of these two portions of capital that can potentially drive company productivity.

One such model that incorporates quantifiable efficiency measurements of intellectual capital, as well as the role of capital employment is the VAIC model (Pulic, 2000). This model's attributes and constituents justify it as the tool of choice within this research as a quantifiable measure of the effect of intellectual capital on firm performance within the South African economy. Further discussion of this model and its make-up will be expanded upon in later sections to further explain its suitability.

Establishing meaningful insights into the effect of intellectual capital on value-creation should yield instructive information into the degree to which it plays a role in firm performance. This should aid management in recognising the importance of effective intellectual capital within a company as well as how to prioritise and allocate resources for its monitoring and management accordingly, dependent on the impact it can provide. It can also aid South African management in establishing whether it is more beneficial to focus on intellectual capital or rather financial and physical capital as a source of sustainable competitive advantage and thus plan its development and investment strategies accordingly. It could also indicate the difference, if any, intellectual capital plays in company performance in developed regions, where significantly more research has been performed, in comparison to South Africa. This could give insights into what approach those wishing to operate in emerging markets as opposed to developed markets should take as well as the state of intellectual capital development across regions.

1.3 Problem statement

The problem under consideration is to analyse the effect of intellectual capital on firm performance of JSE-listed firms. Intellectual capital as a measurable quantity in this context was measured as a function of human and structural capital. The focus of the analysis of Intellectual Capital was around its efficiency in contribution to value-addition of the firm. Firm performance was quantified by traditional performance metrics such as profitability ratios, productivity ratios and market valuation to name but a few. It is worth noting that macroeconomic factors, such as the industry involved or relative company sizes, that may enhance or detract from company performance were considered and their potential effects accounted for.

1.4 Significance of the study

The significance of the study was its aim to expand upon previous analyses to include the effects of structural capital efficiency alongside human capital efficiency, coupled with the efficiency of capital employed in the South African context.

This study aimed to provide insights to those attempting to anticipate future firm performance by analysing firm effectiveness in value-creation through firm intellectual capital practices.

Such insights may aid investors when evaluating investment prospects or managers when they wish to anticipate the future health of their own company, or their competitors from an intellectual capital point-of-view, albeit without the benefit of direct insights into actual implementation practices, which is beyond the scope of this research.

1.5 Delimitations of the study

The study included JSE-listed firms that have posted audited financial results for the years 2001-2017. This included all companies that existed in or prior to 2001 but excluded companies that listed or delisted within this period. Comprehensive details of the complete exclusion criteria and process for firm selection is delineated in theChapter 3. Research Methodology section.

The study utilised the VAIC model and its associated interpretation of intellectual capital but it did not seek to test or make judgements on the VAIC model itself, but rather to glean and interpret any possible insights that may arise from the data and the VAIC model usage. The model controls for those variables that may impact on firm performance that are deemed noteworthy and are prevalent in the foundational literature. However, they are by no means considered to be exhaustive, and these considerations and implications are expounded in the results discussion.

Chapter 2. Literature Review

2.1 Introduction

The importance of intellectual capital within industry is an area that has received much attention, with much of it focusing on firm performance in various regions, utilising a variety of metrics of intellectual capital and definitions of firm performance. The following section reviews existing literature to aid in establishing expected relationships between firm performance and intellectual capital to inform development of prospective relationship hypotheses.

Todericiu and Stăniţ (2015) reviewed the importance of effective intellectual capital application within the knowledge-based economy in Europe, with a focus on Small and Medium Enterprises (SMEs) utilising it as a source of sustainable competitive advantage. They found it to have particular value to SMEs due to their lower financial capital base thus they are more dependent on the efficiency and competency of their internal knowledge.

SMEs utilising intellectual capital as a means of driving innovation, where innovation is defined as, “implementing new ideas that create value” (Kalkan, Bozkurt, & Arman, 2014, p. 702), can prove particularly successful as confirmed by McDowell, Peake, Coder, and Harris (2018). They sampled SMEs across various industries in the USA and they found a positive relationship between intellectual capital and organisational performance with innovativeness linking factor intellectual capital and organisational performance. This holds particularly relevant implications for South African SMEs as they can play a decisive role in economic development, as they are estimated to make up 90% of formal businesses, employ 60% of the South African workforce and account for approximately 30% of Gross Domestic Product (GDP) (The Banking Association of South Africa, 2018). Kalkan et al. (2014) define this link of innovation to intellectual capital as a company’s ability to harness its internal knowledge resources. Kalkan et al. (2014) found that for insurance companies in Turkey intellectual capital, along with innovation and organisational strategy, which are arguably applied components of intellectual capital, again achieved a positive association to firm performance.

The role intellectual capital on firm performance in Portuguese SME hotels was also reviewed by Sardo, Serrasqueiro, and Alves (2018) and they determined that intellectual capital has a positive impact on financial performance, with human and structural capital playing a key role in this particular service sector. In contrast to McDowell et al. (2018) and Kalkan et al. (2014), who used qualitative descriptors of intellectual capital, Sardo et al. (2018) used financial estimates of intellectual capital and came to similar findings. It is also worth noting that whilst the above studies indicate a positive association seemingly irrespective of industry or region, none of them made any attempt to quantify the importance of intellectual capital relative to physical and financial capital. This represents a distinct shortcoming in evaluating the overall performance, health and trajectory of a given company.

As mentioned in the previous section, one of the challenges of evaluating intellectual capital is the difficulty in applying a meaningful value to it due to its intangible make-up and the resulting inability of accounting for it within generally accepted accounting practices (GAAP) (Firer, 2005). Due to this there is no widely accepted measure of intellectual capital performance, however one such tool that seeks to assign a real value to, as well as the effect of, intellectual capital is that of the VAIC framework (Pulic, 2004).

The following sections discuss the historical results of intellectual capital's effect on firm performance through the use of the VAIC tool in South Africa, developed and developing regions. A brief description of the tool will be provided, however a detailed description and review of the tool will be presented subsequently within the Methodology section. The implications gleaned from this collective research are then utilised to inform the proposed hypothesis.

2.2 Intellectual capital effect measurement using the VAIC Model: South African Studies

The VAIC model essentially quantifies intellectual capital by treating total employee costs as the quantifiable measurement of human capital. Structural capital is then calculated as the difference between the total value added, total sales less materials, and human capital. This allows for the use of quantified data from audited financial statements to form the basis of analysis of intellectual capital in a standardised manner (Pulic, 2004).

Some of the earliest research using the VAIC tool in a South African context was performed by Firer and Williams (2003) who evaluated 75 listed SA companies in the 2001 financial period from sectors highly dependent on intellectual capital. The VAIC measurement was evaluated against profitability, productivity and market valuation and they found that associations yielded limited to mixed results for all three factors. Physical capital appeared to still be the most significant factor for value-creation ahead of intellectual capital efficiency (Firer & Williams, 2003).

Firer and Stainbank (2003) also investigated IC performance association with the same three variables mentioned above within the 2001 year however with slightly different company selection criteria. Their results indicated a slight positive relationship of VAIC to predicting profitably, but not conclusively. Furthermore, no statistically significant relationships were observed between VAIC and productivity or market valuation.

The greatest limitations on this preliminary research related to the small sample number as well as a snapshot of just one year. The meaningfulness of VAIC for individual periods could be indeterminable since value-added may vary substantially from year to year (Ståhle, Ståhle, & Aho, 2011), hence the belief that successive years results should be considered to garner more meaningful insights. This is in fact directly mentioned by Firer and Stainbank (2003) as a possible study limitation, and they recommend the use of a longitudinal study to provide greater insights into performance over time and overcome the lag that will be present between investment and observable results as this may exceed one period.

Morris (2015b) sought to address this shortcoming and conducted an evaluation of South African HCE trends with a longitudinal study using a portion of the VAIC framework by reviewing the development of the human capital efficiency component of it for the period 2001-2011. Morris (2015b) determined that there was an overall decline in human capital efficiency for the period due to SA companies' focus on physical resources, significant salary increases as a result of extensive striking, and possibly due to latent effects of the global recession of the 2007-2009 period.

Morris (2015a) then expanded this research and sought to evaluate the effect of human capital efficiency on South African company performance by using the human capital efficiency (HCE) component of the VAIC model only, and thus sought to create a link between companies' ability to create value relative to their employee costs. This was done to determine if this could statistically be considered a company performance differentiator and thus a source of competitive advantage. This study covered the 2001-2011 period and encompassed 390 companies listed on the JSE and Main Board and Alternative Exchange (ALT-X) across the technology, financial, consumer goods and services, industrial and basic materials industries. Company financial performance factors considered were return on assets (ROA), revenue growth (RG) and headline earnings per share (HEPS). Company market performance factors considered were market-to-book ratio (MB) and total share return (TSR) (Morris, 2015a). The study yielded a number of noteworthy findings. Firstly, the study indicated an association between HCE and profitability across all industries considered except for the Technology sector, which displayed HEPS performance with no relation to HCE. HCE was found to have a positive association with ROA for all industries. RG was found to be positively associated with HCE for all non-consumer-driven industries. For consumer industries, HCE does however, aid in profitability. HCE was found to have no bearing at all on market performance (Morris, 2015a).

This study satisfied the recommendations of Firer and Stainbank (2003) from a longitudinal perspective and greatly increased the scope of the number of industries and companies considered to provide significantly more insights into firm performance differentiators related to intellectual capital. However, the fact that it doesn't incorporate intellectual capital efficiency or the VAIC index as a whole indicates that there are potentially additional findings to be made. This study sought to extend the work of Morris (2015a) on intellectual capital as a predictor of firm performance utilising the complete VAIC model for the previous period and in the current South African business and industry landscape to determine if any greater insights can be established.

2.3 Intellectual capital effect measurement using the VAIC Model: International Studies

2.3.1 Developed Markets

Meles et al. (2016) performed an extensive review of over 5,500 commercial banks in the USA over 2005-2012. They established that intellectual capital positively effects financial performance of USA banks, with HCE playing the largest role over other intellectual capital sub-components when considering return on average assets and return on average equity.

Maditinos, Chatzoudes, Tsairidis, and Theriou (2011) on the other hand, could only verify a relationship between HCE and return on equity (ROE), and no other component of the VAIC model was found to be related to market-book value or ROA for 96 companies listed on the Athens stock exchange (ASE) for the period 2006-2008.

Clarke, Seng, and Whiting (2011) evaluated 2,161 listed Australian companies for the period 2003-2008 and found that intellectual capital, and in particular HCE, does display a positive association with firm performance. Its influence however, is secondary to that of financial and physical capital in the Australian market. Also in the Australian market, Joshi, Cahill, Sidhu, and Kansal (2013) focussed on intellectual capital and firm performance specifically in the financial sector. Whilst varying degrees of influence were found across sub-sectors, no association was found between higher Intellectual Capital Efficiency and financial performance, ROA specifically, which was in fact associated with physical capital instead.

2.3.2 Emerging Markets

Chen, Cheng, and Hwang (2005) evaluated listed Taiwanese companies and found that intellectual capital displayed a positive impact on both market value and financial performance, in the form of profitability and revenue growth, for all but 64 firms on the Taiwan Stock Exchange (TSE) for the period 1992-2002. Chen et al. (2005) go so far as to state that intellectual capital has equivalent importance to that of physical capital and advises governments and companies of developing regions to balance investments between the two to achieve sustainable value-creation and competitive advantage.

Alhassan and Asare (2016) evaluated the relationship between intellectual capital and productivity in 18 Ghanaian banks for the period 2003-2011 and found that VAIC displayed a positive association with productivity, and specifically that HCE and Capital Employed Efficiency components are significant drivers of productivity growth in the sector.

The role played by intellectual capital in firm performance amongst listed Thai manufacturing firms was evaluated by Kongkiti, Narongsak, Agnieszka, and Keng-Boon (2011) and was found to play a significant and positive role in firm performance when considering ROE, ROA, revenue growth and employee productivity. Labour productivity also proved positively associated to 350 listed companies in Russia between 2005-2007 (Molodchik & Bykova, 2011), along with profitability and revenue growth.

Intellectual capital impact was evaluated in 20 Malaysian financial institutions for the period 1999-2007 and found to be strongly positively associated with firm profitability, specifically ROA (Ting & Lean, 2009). This positive association to profitability was supported by Nadeem, Gan, and Nguyen (2017), who found a positive association between firm performance and intellectual capital for Brazil, Russia, India, China and South Africa (BRICS) companies collectively in the period 2004-2015 and a strong association with ROA and ROE specifically.

Nuryaman (2015) determined, through an evaluation of 93 manufacturing companies listed on the Indonesian Stock Exchange, that intellectual capital had a positive impact on profitability in the form of ROE, but no significant relationship to ROA or net profit margin. Furthermore, intellectual capital was found to play an intervening role in the causal relationship between profitability and firm value, in the form of price-book value.

2.4 Conclusion of the Literature Review

From the above it appears that intellectual capital is typically positively associated to certain metrics of financial firm performance but not market performance, irrespective of whether qualitative or quantitative metrics are used. Due to the freely available, ratified information on financial performance from audited financial reports, and the ease with which performance metrics can thus be compared across companies, a quantitative approach was deemed preferable as an analysis methodology.

VAIC is a model well-suited to a quantitative evaluation of the effect intellectual capital plays on firm performance. It has been applied fairly extensively across both developed and emerging markets and has displayed varied results as to the degree of impact intellectual capital has on various measures of firm performance. Results appear to display a positive association to profitability, specifically ROA but appear to be typically inconclusive for broader financial performance and market performance metrics. In order to most accurately account for the impact of intellectual capital and its constituents on firm performance, it will be evaluated using the aggregated VAIC value as well as the three constituents that make it up, HCE, Structural Capital Efficiency (SCE), accounted for by means of their combined effect through the total ICE, and CEE to establish the proportional roles played by the sub-components.

2.4.1 IC Impact on Firm Performance Hypotheses

$H1_a$: Changes in VAIC have no effect on firm performance

$H1_b$: Changes in VAIC have an effect on firm performance

$H2_a$: Changes in ICE have no effect on firm performance

$H2_b$: Changes in ICE have an effect on firm performance

$H3_a$: Changes in CEE have no effect on firm performance

$H3_b$: Changes in CEE have an effect on firm performance

The detailed breakdown on the measurements of firm performance, encompassing specific market and financial performance metrics, is outlined in Chapter 3. Research Methodology, and the hypotheses will be evaluated against each of the performance metrics individually.

Chapter 3. Research Methodology

The following section outlines the model for evaluation of the hypotheses reported in the 2.4 Conclusion of the Literature Review.

3.1 Research paradigm

A quantitative method was followed to evaluate the collected data, which were in the form of published audited financial results. This is suitable as the goal of the research was to establish any general observed relationships between IC and firm performance.

3.2 Research Design

Research was evaluated through construction of a statistical model evaluating VAIC and firm performance, similar to the methodology developed by Morris (2015a) to allow for more direct comparison of the results, but building on the model to include the aggregated VAIC measurement as well as all of its sub-components, rather than just the HCE contribution measured by Morris (2015a). This method also bears many similarities to the approaches adopted by Meles et al. (2016) and Nadeem et al. (2017) thereby further aiding in meaningful comparisons, as well as counteracting any observed or stated limitations where it may be feasible.

This was constructed in the form of a panel regression model to be outlined in the 3.8 Data analysis and interpretation section. A panel regression was selected due to its suitability to the longitudinal, cross-sectional multivariate analysis required to analyse the number of variables of concern for an extended period of time.

This statistical model allowed for an effective analysis of the multiple variables of consideration across a significant time-period, allowing for the greatest possibility of meaningful findings and implications.

3.3 Population and sample

3.3.1 Population

The population consisted of all companies listed on the JSE for the period 2001-2017. This included companies listed before or in 2001 but not those that listed or delisted within this period.

3.3.2 Sample and sampling method

The sample consisted of all JSE listed companies that published audited financial results for the periods under consideration. Companies that did not post all the required data for at least 12 of the periods, i.e. 70%, were excluded so as to prevent excessive missing data points within the study to enhance model reliability. Companies that have posted negative operating profits and book values were disregarded due to the VAIC models' inability to measure ICE as per Firer and Stainbank (2003) and Nadeem et al. (2017). Companies that did not post information critical to the model's usage explicitly, for example earnings before interest, tax, depreciation and amortisation (EBITDA), were also excluded so as to avoid any unintentional inconsistency due to reporting and assumption differences. The study was also limited to those companies that published a Value Added Statement so as to utilise a consistent, unambiguous and standardised measure of employee costs since this statement publishes Salaries and Wages as a specific line-item. Companies that have adjusted their financial year-end during the period were also excluded.

3.4 Research Instrument – VAIC Model

3.5 Model Description

“I believe that today ICE is for knowledge work and the knowledge worker what once was productivity for manual work and the manual worker.”, (Pulic, 2004, p. 65). This was the notion that underpinned Ante Pulic’s assertion that an alternative index was required to objectively measure organisations’ ability to create value, rather than traditional indexes based on output-centred productivity. It was with this in mind that he developed the Value-added Intellectual Coefficient.

The fundamental difference in Pulic’s approach on the measurement of intellectual capital to traditional measures is that he treats employee wages as an investment rather than a cost (Pulic, 2000).

Pulic believed this would aid in creating a suitable and impartial intellectual capital-centred performance metric that can evaluate different companies from different industries based on their ability to effectively harness their workforces to achieve success by means of a measurable quantity of value-creation or value-added.

The concept of the value-added by a company is then defined as:

$$\mathrm{VA} = \mathrm{OUT} - \mathrm{IN} \tag{1}$$

Where VA denotes the value added or generated for the company, OUT is the total sales and IN is the total cost of bought-in materials, services and components (Pulic, 2004).

VA can also be determined by:

$$\mathrm{VA} = \mathrm{OP} + \mathrm{EC} + \mathrm{D} + \mathrm{A} \tag{2}$$

Where OP is the operating profit, EC are the total employee costs, D is depreciation and A is amortisation (Pulic, 2004).

VAIC consists of two efficiency aspects, ICE and CEE (Pulic, 2004).

The definition of VA is paramount for the VAIC model as it is the key feature of all efficiency calculations. The physical values that form the basis of the calculation of VAIC are indicated below (Ståhle et al., 2011):

- Human capital (HC) as determined by total employee costs i.e. total salary and wage bill
- Structural Capital (SC) which is determined as the difference between VA and HC
- Capital Employed (CE) which is the company's financial and physical capital defined by the book value of the net assets for the company (Firer & Stainbank, 2003)

HC and SC form the two components of ICE for the model.

The first component of the ICE portion of the VAIC tool is that of HCE which is calculated as:

$$\mathrm{HCE} = \mathrm{VA}/\mathrm{HC} \qquad (3)$$

The second constituent of IC is that of SC, which is calculated as:

$$\mathrm{SC} = \mathrm{VA} - \mathrm{HC} \qquad (4)$$

It is worth noting that SCs value is thus dependent on two fixed values, VA and HC, thus it is a calculated value and not determined from financial statements. This means that it is possible that SC can yield a zero or even negative value depending on HC versus VA.

Structural Capital Efficiency (SCE), the second component of ICE, is defined as:

$$\mathrm{SCE} = \mathrm{SC}/\mathrm{VA} \qquad (5)$$

The complete value of ICE is then determined by:

$$\mathrm{ICE} = \mathrm{HCE} + \mathrm{SCE} \qquad (6)$$

Pulic (2004) states that ICE is the knowledge work equivalent of productivity for manual work.

The other leg of the model is that of CEE as Pulic (2004) proposes that intellectual capital cannot create value in and of itself and thus financial and physical capital efficiency must also be incorporated to evaluate any given company's value creation efficiency(Pulic, 2004).

CEE is defined as:

$$\mathrm{CEE} = \mathrm{VA}/\mathrm{CE} \tag{7}$$

The two components are then summed together to indicate the overall value-creation efficiency of a company through application of its intellectual ability by means of measuring the amount of new value created per unit of money invested.

VAIC is thus finally defined as:

$$\mathrm{VAIC} = \mathrm{ICE} + \mathrm{CEE} \tag{8}$$

A visual summary of the construction of the VAIC through its constituents is indicated in the following figure (Ståhle et al., 2011, p. 534):

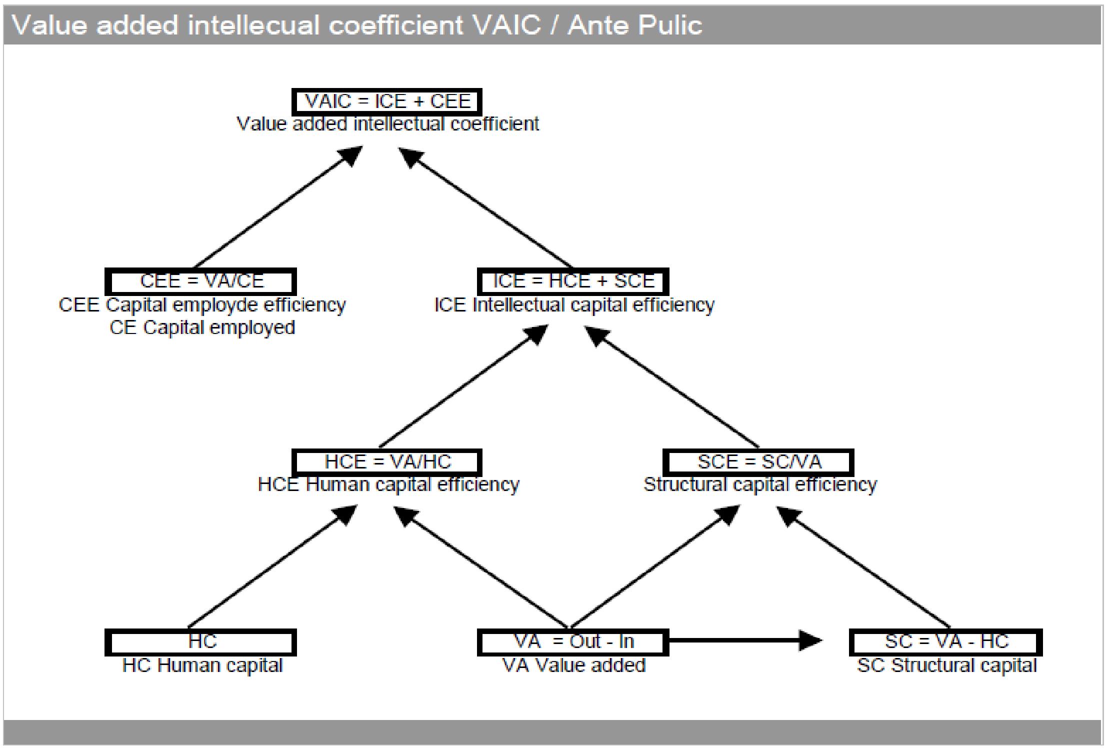

Figure 3: Construction of the VAIC Model[4]

3.6 Model Evaluation

3.6.1 Model Strengths

Apart from the aforementioned benefit of the use of audited financial results assuring data integrity and a practical standardisation of data collection and measurement (Firer & Williams, 2003), it also possesses the benefit of objectivity in that it is based on independently reviewed financial figures according to accounting standards, thus figures cannot be skewed by subjective assumptions (Pulic, 2000).

The standardisation of data collection measurement enables comparison across industries and countries (Firer & Williams, 2003) with only corrections for taxation practices having to be noted.

[4] (Ståhle et al., 2011, p. 534)

Accessing the financial information is also simplified by the fact that preparation of annual financial statements is a legal requirement as per the Companies Act, No. 71 of 2008 (PwC South Africa, 2011) and publication of these results is a JSE requirement (JSE, 2010) thus reliable ongoing access is assured for a substantial portion of the market with only private companies' information not necessarily being readily available. Since this study focussed exclusively on listed companies in South Africa this is not an obstacle.

3.6.2 Model Weaknesses

One notable concern in terms of the stability of the model is that since SC is a result of the difference between VA and HC, where HC are fixed employee costs, there are instances where, should SC be zero or negative, VAIC shall also be zero or negative. A greater risk in terms of meaningful data extraction from VAIC is the case where VA is very similar or equal to HC, in that it can result in an infinite, either positive or negative depending on the sign of VA, VAIC (Ståhle et al., 2011). Any such data would hold no analytical value statistically and thus must be monitored and removed from the final analysis so as not to skew the results.

Another shortcoming is that whilst utilising audited financial results ensures the validity of the information, it does also mean that the results are subject to the accounting practices and decision making of the company in question (Ståhle et al., 2011). The greatest impact where this may be seen is in the calculation of VA where companies' depreciation and amortisation practices may differ which could over- or underestimate the VA of companies relative to one another.

A final weakness to the model is that it does not incorporate the relational capital component of IC at all so its measurement practices are not all encompassing in terms of the traditional definition of the components of IC.

For the context of this study a deviation from the traditional IC definition was not deemed noteworthy since the focus of the study is the role that IC plays in firm performance and the VAIC is still deemed the most suitable tool to establish meaningful quantitative insights despite its conceptual misalignment to traditional IC definitions.

3.7 Procedure for data collection

Data was collected per firm for the specific financial measures of interest through the use of the INET FAS system and the IRESS Expert database accessed through the Wits Library Database. The detailed process of the data collection, selection and refinement is indicated below.

3.7.1 Data Collection and Selection Process

1. Financial Performance data was collected from the INET FAS system database. The specific data related to: HEPS; Return on Total Assets (ROTA); Market Capitalisation (MC); RG; MB; Debt Ratio (DR); ROE; Total Share Return (TSR); CE; EBITDA
2. Refine company selection based on availability of above data for full period.
3. Download Financial Statements for companies listed from step 2 from IRESS Expert Database. This specific data related to: Income Statement; Balance Sheet; Cash Flow Statement; Value Added Statement.
4. Refine company selection based on employee wage and salary reporting on value added statement.
5. Extract employee costs from value added statement
6. Calculate
    - VA = EBITDA + EC
    - HCE = VA/EC
    - SC = VA – EC = EBITDA
    - SCE = SC/VA
    - ICE = HCE + SCE
    - CEE = VA/CE
    - VAIC = ICE + CEE
7. Missing data processing:
    - If 12 years or more worth of data (70% of periods) was present, missing data was interpolated using the built-in cubic splines interpolation function of Eviews (IHS Markit, 2017a) wherever the data allowed.
    - This resulted in 43 qualifying companies being eligible for the complete study and 721 observations per variable for consideration.

3.8 Data analysis and interpretation

Data was analysed with the use of a panel regression model as was previously mentioned. The makeup of the model is expanded upon below. Selection of dependent and control variables was performed to be in-line with those adopted by Morris (2015a) and Firer and Stainbank (2003) for more accurate comparison in the South African context. The dependent variables represent the selected measures of firm financial and market performance. The control variables incorporate mitigating considerations deemed noteworthy such as the size of the company, the industry within which it operates, the degree of operating risk i.e. to what degree is it leveraged and it's return on equity when considering market performance.

3.8.1 Dependent Variables

- Return on Assets (ROA)
- Revenue Growth (RG)
- Headline Earnings per Share (HEPS)
- Market-to-book ratio (MB)
- Total Share Return (TSR)

3.8.2 Independent Variables

- Value Added Intellectual Coefficient (VAIC)
- Human Capital Efficiency (HCE)
- Structural Capital Efficiency (SCE)
- Capital Employed Efficiency (CEE)

3.8.3 Control Variables

Control variables are selected on the basis

- Debt ratio (DR)
- Firm size as defined by the natural log of the total market capitalisation (LMC)
- Operating Industry (IND)
- Return on Equity (ROE) for MB and TSR

3.8.4 Panel Regression Model

The panel model will follow the form (Brooks, 2008):

$$y_{it} = \alpha + \beta x_{it} + u_{it} \qquad (9)$$

Where y_{it} represents the dependent variable, α is the intercept term, β is the parameter to be estimated on the explanatory variables, x_{it} represents the independent or control variable under consideration for firm i in period t and u_{it} represents the disturbance term (Brooks, 2008).

Written explicitly for considering all dependent variables against VAIC it would be stated as:

$$ROA_{it} = \alpha + \beta_1(VAIC)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (10)$$

$$RG_{it} = \alpha + \beta_1(VAIC)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (11)$$

$$HEPS_{it} = \alpha + \beta_1(VAIC)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (12)$$

$$MB_{it} = \alpha + \beta_1(VAIC)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \qquad (13)$$

$$TSR_{it} = \alpha + \beta_1(VAIC)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \qquad (14)$$

$$ROA_{it} = \alpha + \beta_1(ICE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (15)$$

$$RG_{it} = \alpha + \beta_1(ICE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (16)$$

$$HEPS_{it} = \alpha + \beta_1(ICE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \qquad (17)$$

$$MB_{it} = \alpha + \beta_1(ICE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \qquad (18)$$

$$TSR_{it} = \alpha + \beta_1(ICE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \quad (19)$$

$$ROA_{it} = \alpha + \beta_1(CEE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \quad (20)$$

$$RG_{it} = \alpha + \beta_1(CEE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \quad (21)$$

$$HEPS_{it} = \alpha + \beta_1(CEE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \varepsilon_{it} \quad (22)$$

$$MB_{it} = \alpha + \beta_1(CEE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \quad (23)$$

$$TSR_{it} = \alpha + \beta_1(CEE)_{it} + \beta_2(DR)_{it} + \beta_3(LMC)_{it} + \beta_4(IND)_{it} + \beta_5(ROE)_{it} + \varepsilon_{it} \quad (24)$$

The tool utilised to develop the panel regression models was Eviews 10. To ensure the most appropriate panel model was selected, the following sequence of models, tests and data transformations were performed (Brooks, 2008; IHS Markit, 2017a, 2017b; Startz, 2015):

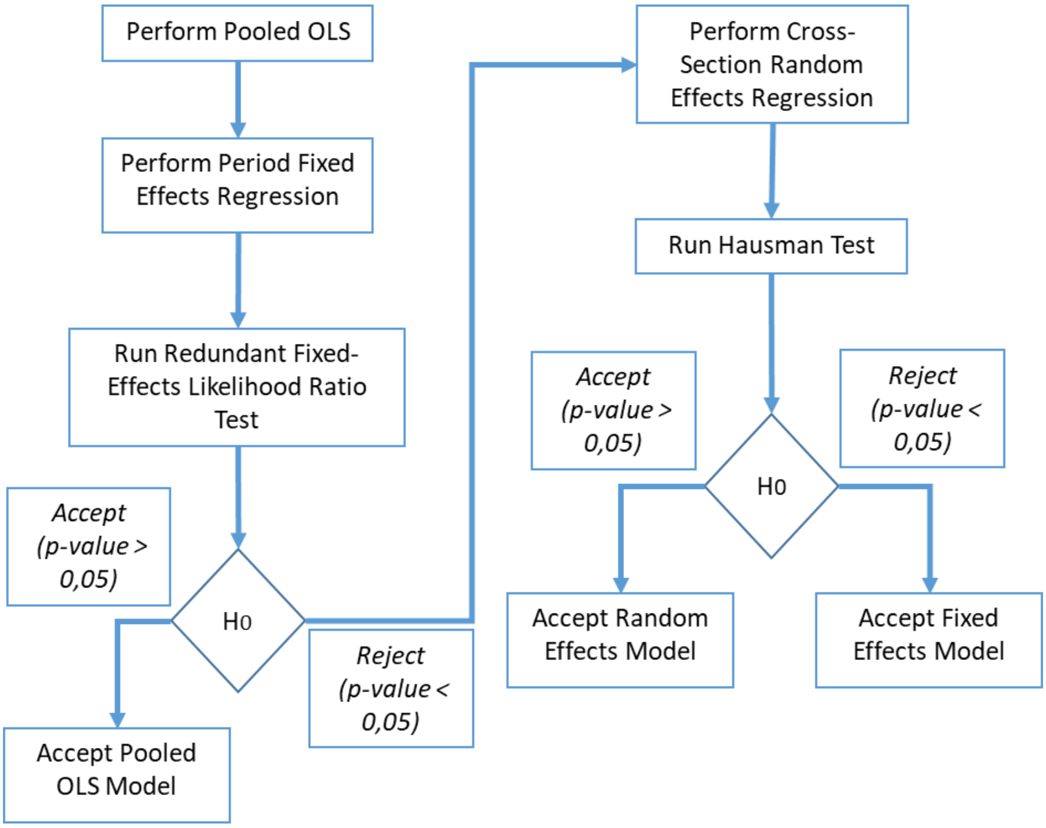

Figure 4: Panel Regression Model Development and Selection Process Flow

The above flow of processing will be performed on each and every regression individually to ensure that the individual models have optimum reliability and applicability.

3.9 Limitations of the study

- Relational capital is not incorporated in the VAIC model. This could lead to an inadequate account of the complete, broadly accepted definition of intellectual capital and thus limit holistic consideration thereof.
- Companies with negative performance are excluded due to the model's make-up, limiting inferences that may have been possible on underperforming firms.
- Removal of companies that delist within the period potentially introduces the risk of survivorship bias and this will have to be incorporated on any associations noted.
- Removal of companies that list within the period may limit the analysis of companies entering within the knowledge worker age and thus would potentially have a heavier reliance on human capital and its implications.
- There is a risk of invalid values of VAIC where VA is nearly or equal to HC. This will need to be monitored and the data rectified accordingly so as to mitigate the risk of outliers and noisy data.
- The selection of only companies that publish Value Added statements allows for standardised analysis but introduces a bias towards companies that deem this a statement worthy of reporting, potentially eliminating companies from which valid insights and relationships could otherwise be drawn.
- The strict exclusion criteria for data selection allows for a more robust dataset however it does greatly reduce the number of cross-sections present, however this is anticipated to be ameliorated due to the construction of a panel approach and its associated increased number of observations.

3.10 Validity and reliability

The primary validity items relating to the VAIC model have already been delineated within the Model Strengths and Model Weaknesses sections and are not restated to avoid redundancy. However, further noteworthy considerations are discussed in the following sections.

3.10.1 External validity

The study achieves external validity to a broader South African context, since a variety of industries, company ages and operating profiles are encompassed within the dataset. Thus the participant characteristics should allow generalisability to the broader range of South African companies that don't meet the required data-collection criteria for the purposes of this exercise. The time frame selected represents the longest period in a South African context in any of the aforementioned research (Firer, 2005; Firer & Stainbank, 2003; Firer & Williams, 2003; Morris, 2015a, 2015b) The setting of the research is not of concern for external validity since the foundation of the data-capturing, and thus analysis, is based on audited financial results so the data is based on true, real world performance as reported by the IRESS Expert database and INET FAS system. It is worth noting that IRESS Expert as a resource is particularly useful as it exclusively uses annual audited financial data of listed entities, standardises the data and calculates 42 standard financial ratios, making it ideal for consistent, standardised data collection (De Jager, 2008).

It's noted that whilst there are different reporting assumptions used for IRESS and INET, e.g. ROE with vs. without intangibles, using the different databases consistently for the same metric will alleviate any inherent risks since consistent reporting methods will always be used for any given value, thus it won't materially impact the relationship between values. This should be further smoothed by the fact that only ratios are used for all values except market capitalisation which is addressed by using its natural log so as to decrease the impact of relative magnitude.

The selection of the metrics of financial performance, to yield meaningful insights, was based on the most common metrics used in historical research across various regions, industries and time frames (Alhassan & Asare, 2016; Chen et al., 2005; Firer, 2005; Firer & Stainbank, 2003; Firer & Williams, 2003; Maditinos et al., 2011; Meles et al., 2016; Morris, 2015a, 2015b; Nadeem et al., 2017; Ståhle et al., 2011).

3.10.2 Internal validity

From a construct validity perspective (Wits Business School, 2017) the use of the VAIC model has shortcomings in that it does not completely cover all the definition requirements of traditional intellectual capital. However, the lack of standardisation on measurements of intellectual capital as well as the aforementioned inconsistencies in disclosure practices (Wagiciengo & Belal, 2012) mean that the VAIC is judged to be the most suitable objective quantitative measure of intellectual capital, although it is noted that it is in essence a proxy measure for it. The empirical validity of VAIC as a measure of intellectual capital has been confirmed by Ghosh and Maji (2015) however, it should be noted that structural capital as it is defined in VAIC, and by extension SCE, is often criticised as an inappropriate means of accurately measuring structural capital. (Chen et al., 2005; Ghosh & Maji, 2015; Nadeem et al., 2017) However, criticism of the aspects of the VAIC tool itself are deemed beyond the scope of the investigation but any relevant implications will still be noted during the discussion.

3.10.3 Reliability

The selection of a panel regression as the statistical methodology holds three distinct reliability benefits. Firstly, it enables for a more complex analysis than merely individual longitudinal or cross-sectional analyses. Therefore it has the potential to more accurately indicate interdependencies and relationships, as well as allowing for a more thorough means of control to account for potential sources of noise (Brooks, 2008). Secondly, panel data allows for decreased regression errors where there is what would ordinarily be insufficient time-series depth, typical for econometric analyses (De Jager, 2008). This is true since the combination of time-series and cross-sectional data increases the number of degrees of freedom by means of incorporating the interactive behaviour of multiple firms at the same time. The combination of data can also ameliorate potential multicollinearity issues that may occur in individual time-series models (Brooks, 2008). Thirdly, correct model structuring can eliminate some forms of omitted variable bias (Brooks, 2008).

However, it is noted that the risk of omitted variable bias (De Jager, 2008) is present for certain dependent variables. As a specific example it is noted that HEPS could be significantly influenced by market sentiment (Morris, 2015a) and RG could be significantly influenced by inflation and exchange rates (De Jager, 2008). For model practicality reasons the control variables are not exhaustive, however influencing factors not accounted for in the model are considered during the discussion of the results.

It is noted that all data under consideration are essentially ratios, thus errors due to differing orders of magnitude are likely to be ameliorated and allow for more direct relationship realisation. The only exceptions to this are market capitalisation and HEPS. It is for this reason that the natural logarithm of market capitalisation was taken to mitigate this risk to reliability (Morris, 2015a). The variation in HEPS will be considered within the model and adjusted as necessary should the magnitude range appear to have a significant impact, however since this is the dependant variable rather than an explanatory variable it is not anticipated that its magnitude will have a meaningful impact on reliability. If a natural logarithm transformation is deemed necessary, any negative values will be addressed by taking the log of the absolute value and then correcting it back to a negative value.

The reliability of the results gathered through the VAIC tool are anticipated to be high. This is due to the fact that the data is secondary and based on published, audited financial results (Pulic, 2004) thus it will satisfy stability and equivalence requirements and will remain accurate and precise (Wits Business School, 2017).

Furthermore, various relevant statistical treatments will be performed to ensure data integrity. Normality of data considerations were not deemed relevant as there is no need for such an econometric study to have normally distributed data (Startz, 2015). Heteroskedasticity and serial correlation of the data will be monitored and corrected for using appropriate Generalised Least Squares (GLS) techniques appropriate for panels (Brooks, 2008; IHS Markit, 2017a, 2017b; Startz, 2015). The detailed flow of the statistical tests performed and any required resultant transformations are listed in the figure below:

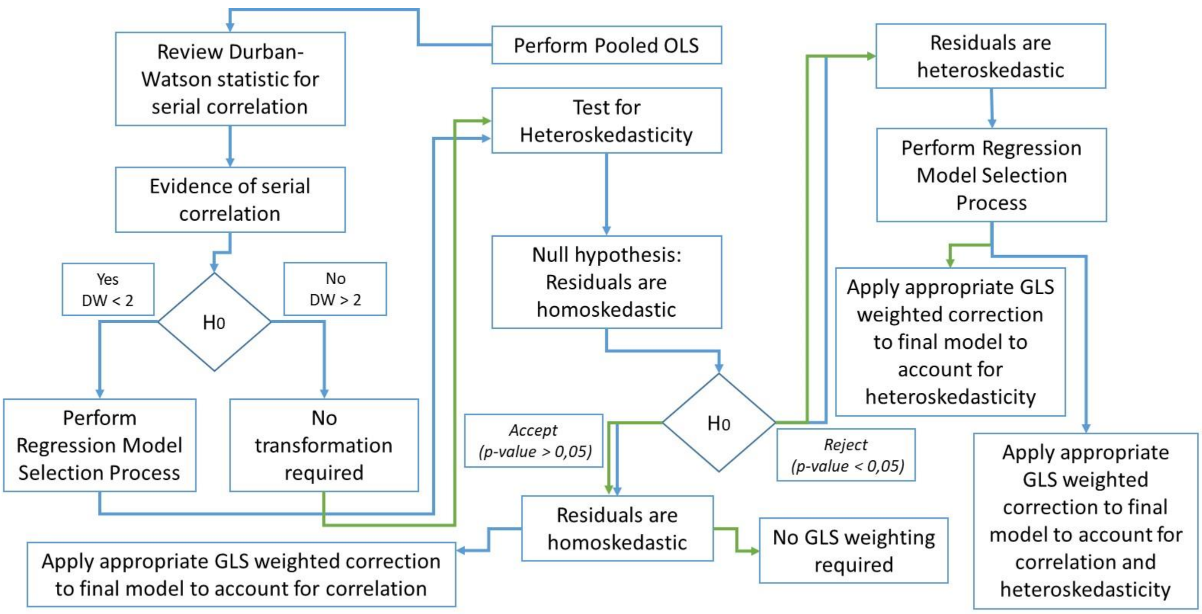

Figure 5: Data Reliability Improvement Review and Correction Process Flow

To enhance the analytical capacity of the model data transformations and appropriate GLS techniques could also be utilised where the model initially does not achieve statistical significance, where statistical significance was evaluated at a 5% significance. The figure below indicates flow for transformation and corrections to improve model integrity and significance.

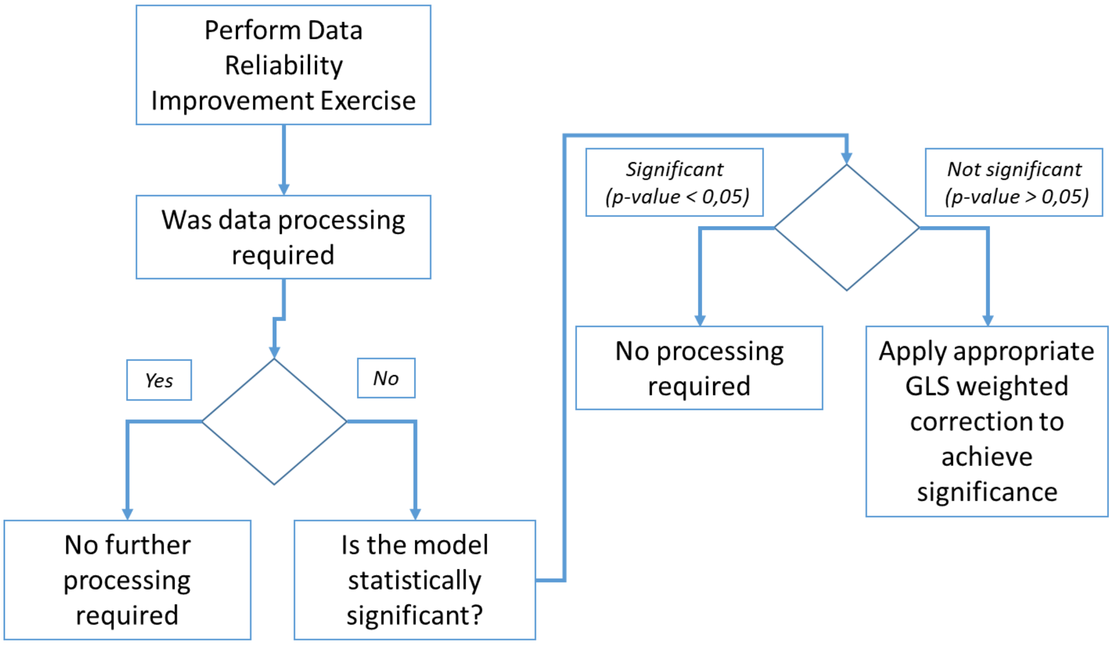

Figure 6: Model Significance Review and Correction Process Flow

The detailed transformations will be clearly indicated within the results on a case by case basis along with their associated justifications and implications.

There is no inherent data selection bias since all JSE listed companies are to be considered and are rejected only on the basis of the suitability of the data for analysis. The implications of the data selection and exclusion process are clearly indicated in the discussion of the 3.9 Limitations of the study and are thus not re-stated to avoid redundancy.

3.11 Ethical Considerations

From a data collection and data processing perspective no specific ethical considerations were deemed noteworthy as there were no inherent biases in the presentation of the data, since it comes from an audited source. Companies were only excluded based on the suitability of the data to the model rather than any other determining factor such as a preference for manufacturing or finance. The presentation and discussion of the results was handled in an objective, impartial manner so as to not unfairly bias readers towards deciding, from a research conclusion implications perspective, on whether to focus on intellectual capital development or physical capital development. Rather, the results were presented and discussed to indicate what, if any, role intellectual capital plays in firm performance in various contexts, and allow readers to make their own judgements as to how best to proceed in their respective context. This was deemed noteworthy as a potential unintended consequence of the research would be for companies to adjust their operating practices from a labour development perspective in a manner that may be detrimental to the company. This could be either in the form of a misalignment of skilled versus unskilled labour allocation, a disproportionate commitment of funds to training with unrealistic firm performance growth expectations, or conversely, decreasing developmental initiatives and focusing on physical capital investment. The risk of this was mitigated through emphasising any limitations and shortcomings of the research as well as clearly indicating the rationale behind assertions to allow the reader to make their own judgements in an informed manner.

Individual company's performance or practices were also not stated but rather only the outcomes of the data analysis as a whole. This is to avoid any risk of either promoting or criticising individual companies or practices.

Chapter 4. Results

The following section details the outcomes of the data collection, processing and analysis. First a brief overview of the descriptive statistics is indicated, followed by the results of the individual panel regressions listed in the 3.8.4 Panel Regression Model. The results for the pooled ordinary least squares (OLS), fixed-effects and random effects models as well as results of the related selection tests, as outlined in Figure 4, are consolidated into individual tables for easier reading and evaluation. The respective panel regression methods utilised to ensure model reliability are indicated within the respective tables and were selected as per the process defined in Figure 5 and Figure 6. Brief descriptions of the results of the regressions are included herein but the detailed discussions and corresponding implications are expounded in the Chapter 5. Discussion of Results section.

4.1 Descriptive Statistics

The table below indicates the consolidated descriptive statistics of all variables after the inclusion of cubic spline interpolation data. To provide clarity on the model constituents and make up, the number of common observations per variable are indicated. Based on the available data the panel is unbalanced.

Table 2: Model Data Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
CEE	0.66	0.59	2.51	0.04	0.35	1.23	5.44	721
DR	0.50	0.20	45.22	-12.50	2.48	14.21	245.26	721
ICE	3.19	2.59	14.44	1.06	1.77	2.26	9.37	721
HEPS	235.29	93.20	2773.00	-1880.00	424.85	1.53	9.98	721
LMC	7.48	7.59	12.14	1.10	2.50	-0.29	2.20	721
MB	6.96	1.90	2277.81	-14.33	85.22	26.31	701.29	721
RG	0.18	0.11	22.36	-0.95	1.00	17.65	363.61	721
ROA	0.10	0.10	5.15	-1.45	0.25	10.91	248.57	721
ROE	0.29	0.16	169.27	-145.26	8.41	4.13	351.94	721
TSR	0.41	0.15	56.92	-1.31	3.03	15.73	268.61	721
VAIC	3.85	3.35	14.81	1.40	1.70	2.24	9.55	721

Based on the mean and median ROAs it is clear that South African companies managed to secure moderate returns on assets for the full period. Financial performance metrics such as

ROE and TSR both indicate that the sample of firms considered provided good returns to investors for the period and the RG figures indicate that firms considered stable growth well above average inflation for the period (The World Bank, 2018c) indicating that the majority of firms considered enjoyed genuine growth. The DR performance of the firms indicate that this growth was achieved with a fairly low degree of leverage. This is also supported by the HEPS of the firms sampled and the net effect of this is the positive share valuation that the firms have achieved as is indicated by the mean and median MB ratios. This good performance was achieved in spite of prevailing economic stagnation as indicated by the average GDP growth of 2.81% for the period (The World Bank, 2018a). The financial performance metrics typically display both positive skewness and leptokurtosis, however non-normality is typical in financial ratios (Barnes (1982); Deakin (1976); So (1987) as cited in Morris (2015a)) and thus is acceptable and since there is no requirement for variable normality in regressions (Startz, 2015) no further raw data processing is required relating to these considerations.

It's noteworthy that based on the VAIC values the firms managed to extract significant value from the combined impact of intellectual capital and financial capital. However, approximately 80% of this value add as defined by VAIC was achieved by intellectual capital rather than financial capital. The inter-relationships between different variables will next be considered through a correlation analysis.

4.2 Correlations

The table below indicates the correlations between the various model variables. Results statistically significant at a 95% confidence level are typed in bold. It is noteworthy that very few statistically significant correlations exist within the model. As expected, due to the model construction and based on the calculated values summarised in the descriptive statistics, strong positive correlations exist between VAIC and ICE, however this won't impact the analysis since they are evaluated separately. The same is true for the strong positive correlation between MB and ROA. There are no excessively strong correlations noted between any of the dependent, independent or control variables with the exception on the mildly strong correlation between HEPS and ROA, this will be noted during the regression analysis. It is also noteworthy that there are no preliminary indicative associations between VAIC or ICE and the noted financial performance metrics, with only CEE indicating a very weak positive correlation to ROA.

Table 3: Model Variables Correlation Table

	CEE	DR	ICE	HEPS	LMC	MB	RG	ROA	ROE	TSR	VAIC
CEE	1.000										
DR	-0.048	1.000									
ICE	**-0.294**	-0.058	1.000								
HEPS	-0.026	-0.016	0.001	1.000							
LMC	0.041	0.044	0.013	**0.502**	1.000						
MB	0.067	-0.006	-0.018	-0.017	0.028	1.000					
RG	0.059	0.008	0.009	-0.002	-0.013	-0.033	1.000				
ROA	**0.093**	-0.004	-0.011	**0.074**	-0.003	**0.764**	0.011	1.000			
ROE	0.002	-0.001	0.023	0.005	-0.011	0.029	-0.003	0.005	1.000		
TSR	0.042	0.005	-0.039	-0.029	**-0.096**	0.006	0.061	0.025	0.001	1.000	
VAIC	**-0.103**	-0.070	**0.981**	-0.004	0.021	-0.006	0.022	0.008	0.024	-0.032	1.000

The panel regressions to follow will indicate the relative impact of the VAIC, ICE and CEE on financial performance when considering all indicated control factors holistically.

4.3 VAIC Panel Regression Results

The following regression tables display the consolidated results for equations 10 to 14 individually when applying the panel methods indicated in Figure 4. It is noted that fixed-effects are only considered with regards to period as the usage of industry dummy variables leads to perfect multicollinearity when attempting to apply cross-sectional fixed-effects, thus it is not computationally feasible. The results of the method selection tests are displayed at the base of the table. The following table indicates the regression results considering ROA against VAIC. The format of the table presentation has been adapted from Molele (2018).

Table 4: Results of Panel Regression of ROA and VAIC with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-Section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 10:				
Intercept	0.0537 (0.0000)	0.0641 (0.0113)	-0.0989 (0.2673)	0.0493 (0.3820)
VAIC	-0.0014 (0.2390)	-0.0010 (0.6995)	0.0032 (0.6509)	-0.0020 (0.7163)
DR	-0.0003 (0.8355)	-0.0008 (0.8084)	0.0038 (0.2789)	-0.00045 (0.9041)
LMC	0.0047 (0.0000)	0.0036 (0. 0618)	0.0186 (0.0016)	0.0055 (0.1804)
IND = Basic Industries	-0.0087 (0.3345)	-0.0062 (0.7449)	-0.0128 (0.8683)	-0.0282 (0.5092)
IND = Consumer Goods	0.0049 (0.4732)	-0.0038 (0.8370)	0.0335 (0.6552)	0.0050 (0.9047)
IND = Consumer Services	0.0426 (0.0000)	0.0312 (0.0894)	0.1262 (0.0886)	0.0780 (0.0617)
IND = General Industrials	0.0253 (0.0001)	0.0274 (0.1113)	0.0340 (0.6266)	0.0099 (0.7979)
Adjusted R^2	0.0873 (0.0000)	0.0286 (0.0061)	0.0101 (0.0471)	0.0075 (0.0890)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 1.831; P-value = 0.0240 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 22.926;** P-Value = 0.000 **Decision: Reject H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

Based on the above tests the fixed-effects model is judged to be the correct panel method to apply. Based on the results the model is statistically significant but has little explanatory power overall based on the R^2 value. Specifically, there exists no statistically significant relationship between VAIC or ROA with only LMC displaying a statistically significant weak association with it.

The following table summarises the regressions associated with RG when considered against VAIC.

Table 5: Results of Panel Regression of RG and VAIC with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 11:				
Intercept	0.0861 (0.0231)	0.0774 (0.2041)	0.0212 (0.9268)	0.0212 (0.9269)
VAIC	0.0024 (0.5554)	-0.0048 (0.4572)	0.0103 (0.6544)	0.0103 (0.6550)
DR	0.0044 (0.1186)	0.0035 (0.5330)	0.0041 (0.7856)	0.0041 (0.7860)
LMC	-0.0025 (0.3465)	0.0102 (0.0260)	0.0021 (0.8985)	0.0021 (0.8987)
IND = Basic Industries	0.0602 (0.0218)	0.0622 (0.1752)	0.0962 (0.5820)	0.0962 (0.5826)
IND = Consumer Goods	0.0227 (0.4029)	0.0024 (0.9565)	0.0999 (0.5564)	0.0999 (0.5571)
IND = Consumer Services	0.0429 (0.1528)	0.0698 (0.1140)	0.1729 (0.3099)	0.1729 (0.3107)
IND = General Industrials	0.0655 (0.0039)	0.0493 (0.2349)	0.1729 (0.3099)	0.0748 (0.6380)
Adjusted R^2	0.0128 (0.0232)	0.0417 (0.0004)	0.0748 (0.6374)	-0.0071 (0.9665)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 2.6785; P-value = 0.0004 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 4.928;** P-Value = 0.1771 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

Based on the acceptance tests the Random effects model considering the effect of firms is deemed as the appropriate model when evaluating revenue growth. However, the model overall is not statistically significant nor does it have any explanatory power.

The table below considers the results of firm earnings in the form of HEPS when considered against VAIC.

Table 6: Results of Panel Regression of HEPS and VAIC with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR)	Fixed Effects Model with period effects Method: Panel Least Squares	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 12:				
Intercept	-401.7253 (0.0000)	-602.6157 (0.0000)	-664.2526 (0.0000)	-597.9321 (0.0000)
VAIC	-0.6491 (0.8791)	4.1827 (0.6150)	-14.8542 (0.1569)	2.9774 (0.7156)
DR	-3.9191 (0.0043)	-7.5862 (0.1709)	-6.2696 (0.1908)	-8.1190 (0.1353)
LMC	66.3332 (0.0000)	86.1616 (0.0000)	102.2124 (0.0000)	86.2769 (0.0000)
IND = Basic Industries	110.3024 (0.2031)	193.6662 (0.0020)	189.4083 (0.2160)	193.7977 (0.0019)
IND = Consumer Goods	285.9146 (0.0006)	343.4206 (0.0000)	352.4824 (0.0171)	342.554 (0.0000)
IND = Consumer Services	86.6141 (0.2893)	131.3742 (0.0317)	184.8214 (0.2010)	131.5017 (0.0306)
IND = General Industrials	94.2863 (0.2277)	161.8555 (0.0044)	161.0241 (0.2425)	160.3521 (0.0048)
Adjusted R^2	0.2612 (0.0000)	0.2854 (0.0000)	0.1547 (0.0000)	0.2906 (0.0000)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 11.18; P-value = 0.8021 Decision: Accept H_0: Pooled OLS Model **Hausman Test Chi-Sq. Statistic = 4.4869;** P-Value = 0.2135 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

Considering the above, the random effects model when accounting for the effects of individual firms is the most appropriate method. Based on the above the model has fairly substantial explanatory power as indicated by the R^2 and it is statistically significant overall. Industry type appears to have a strong positive association with HEPS performance based on the relevant βs, with consumer goods industries seeming to typically display the best HEPS performance for the period. It is noteworthy that VAIC has a very small β compared to the other variables and it is not statistically significant either.

The following table displays the regression results when evaluating MB versus VAIC.

Table 7: Results of Panel Regression of MB and VAIC with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 13:				
Intercept	-6.3820 (0.0000)	1.0624 (0.4589)	-21.3907 (0.3236)	-14.4099 (0.4661)
VAIC	0.0291 (0.6696)	-0.1823 (0.2232)	-0.7464 (0.7204)	-1.1634 (0.5522)
DR	-0.0231 (0.5792)	-0.0610 (0.6981)	-0.2218 (0.8627)	-0.2521 (0.8460)
LMC	0.9224 (0.0000)	0.6025 (0.0000)	2.8650 (0.0657)	2.3262 (0.1062)
IND = Basic Industries	1.7081 (0.0000)	1.2785 (0.2328)	2.7237 (0.8708)	1.9303 (0.8963)
IND = Consumer Goods	1.1076 (0.0000)	1.0942 (0.2912)	5.2008 (0.7493)	3.7560 (0.7943)
IND = Consumer Services	3.2656 (0.0000)	2.0620 (0.0468)	23.2179 (0.1540)	21.2168 (0.1423)
IND = General Industrials	3.2074 (0.0000)	3.4960 (0.0004)	7.3809 (0.6275)	6.0973 (0.6507)
ROE	0.0621 (0.2514)	-0.0104 (0.7466)	0.3024 (0.4171)	0.3119 (0.4118)
Adjusted R^2	0.3245 (0.0000)	0.0927 (0.0000)	0.0082 (0.6574)	-0.0028 (0.6479)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 1.8543; P-value = 0.0217 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model				
Hausman Test Chi-Sq. Statistic = 16.3002; P-Value = 0.0026 **Decision: Reject H_0: Random Effects Model (Firm); thus accept H_1: Fixed Effects Model**				
Hausman Test Chi-Sq. Statistic = 2.5957; P-Value = 0.9571 **Decision: Accept H_0: Random Effects Model (Period)**				

Both fixed-effects when accounting for firms or random effects considering the effect of periods are acceptable for the above analysis. Whilst the random effects model is not statistically significant, the fixed-effects model is significant but displays little overall explanatory power as only three of the variables, specifically LMC and the general industrials and consumer services dummy variables, have statistically significant associations with MB.

The following table indicates the results when considering TSR and VAIC.

Table 8: Results of Panel Regression of TSR and VAIC with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 14:				
Intercept	0.3109 (0.0039)	0.2476 (0.0466)	1.3722 (0.1804)	1.5964 (0.0226)
VAIC	-0.0077 (0.4679)	-0.0043 (0.7359)	-0.0054 (0.9499)	-0.0188 (0.7849)
DR	0.0089 (0.1314)	0.0065 (0.5819)	0.0080 (0.8589)	0.0044 (0.9226)
LMC	-0.0194 (0.0441)	0.0051 (0.5871)	-0.1358 (0.0515)	-0.14758 (0.0038)
IND = Basic Industries	0.1313 (0.0414)	0.1279 (0.1721)	-0.0185 (0.9829)	-0.0446 (0.9318)
IND = Consumer Goods	0.0616 (0.3033)	0.0947 (0.2933)	-0.1792 (0.8291)	-0.2257 (0.6556)
IND = Consumer Services	0.0266 (0.6691)	0.1053 (0.2426)	-0.3798 (0.6445)	-0.4310 (0.3963)
IND = General Industrials	0.1405 (0.0095)	0.2139 (0.0119)	0.4564 (0.5560)	0.4124 (0.3835)
ROE	0.0011 (0.7526)	0.0052 (0.7308)	0.0004 (0.9737)	-0.0021 (0.8750)
Adjusted R^2	0.0132 (0.0256)	0.0766 (0.0000)	-0.0028 (0.6473)	0.0092 (0.0676)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 4.3893; P-value = 0.000 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 1.7584;** P-Value = 0.7801 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

From the above the random-effect model accounting for firm effects is the accepted analysis. The model again possesses little explanatory power and is not statistically significant.

4.4 ICE Panel Regression Results

The following regression tables display the consolidated results for equations 15 to 19 individually when applying the panel methods indicated in Figure 4. The table below considers ROA against ICE, or the purely intellectual capital portion of the overall VAIC model.

Table 9: Results of Panel Regression of ROA and ICE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 15:				
Intercept	0.0570 (0.0000)	0.0642 (0.0093)	-0.0903 (0.3037)	0.0538 (0.3277)
ICE	-0.0019 (0.0815)	-0.0012 (0.6451)	0.0015 (0.8332)	-0.0036 (0.5070)
DR	-0.0003 (0.8442)	-0.0008 (0.8102)	0.0037 (0.2864)	-0.0005 (0.8975)
LMC	0.0046 (0.0000)	0.0036 (0.0621)	0.0187 (0.0015)	0.0055 (0.1782)
IND = Basic Industries	-0.0103 (0.2518)	-0.0061 (0.7450)	-0.0143 (0.8531)	-0.0284 (0.5050)
IND = Consumer Goods	0.0031 (0.6496)	-0.0038 (0.8362)	0.0316 (0.6732)	0.0038 (0.9270)
IND = Consumer Services	0.0408 (0.0000)	0.0310 (0.0914)	0.1260 (0.0892)	0.0774 (0.0636)
IND = General Industrials	0.02335 (0.0002)	0.0270 (0.1158)	0.0320 (0.6478)	0.0080 (0.8365)
Adjusted R^2	0.0895 (0.0000)	0.0286 (0.0056)	0.0099 (0.0049)	0.0079 (0.0803)
Redundant Fixed Effects (Period) Likelihood Ratio Test Chi-Sq. Statistic = 1.8434; P-value = 0.0228 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 22.76;** P-Value = 0.0000 **Decision: Reject H_0: Random Effects Model (Firm); thus accept H_1: Fixed Effects Model** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

The accepted model of fixed-firm-effects, despite being significant, displays very little explanatory power with none of the explanatory variables indicating any statistically significant variables.

The following table considers ICE's impact on RG.

Table 10: Results of Panel Regression of RG and ICE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 16:				
Intercept	0.0908 (0.0110)	0.0812 (0.1692)	0.0536 (0.8113)	0.0536 (0.8115)
ICE	0.0010 (0.7874)	-0.0061 (0.3138)	0.0028 (0.8977)	0.0028 (0.8979)
DR	0.0044 (0.1240)	0.0035 (0.5314)	0.0038 (0.8010)	0.0038 (0.8013)
LMC	-0.0023 (0.3841)	0.0100 (0.0278)	0.0026 (0.8762)	0.0026 (0.8764)
IND = Basic Industries	0.0608 (0.0199)	0.0622 (0.1726)	0.0908 (0.6028)	0.0908 (0.6033)
IND = Consumer Goods	0.0219 (0.4183)	0.0015 (0.9730)	0.0926 (0.5851)	0.0926 (0.5857)
IND = Consumer Services	0.0446 (0.1400)	0.0684 (0.1209)	0.1728 (0.3104)	0.1728 (0.3112)
IND = General Industrials	0.0643 (0.0047)	0.0464 (0.2624)	0.0662 (0.6769)	0.0662 (0.6774)
Adjusted R^2	0.0121 (0.0277)	0.0425 (0.0003)	-0.0074 (0.9751)	-0.0074 (0.9751)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 2.7129; P-value = 0.0003 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 4.7559;** P-Value = 0.1906 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

From the above the accepted model is that of the random effects model considering the effect of firms, however neither the model nor the relationship to ICE are statistically significant.

The table below displays the results of ICE's effect on HEPS.

Table 11: Results of Panel Regression of HEPS and ICE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 17:				
Intercept	-405.2188 (0.0000)	-451.8374 (0.0000)	-674.1395 (0.0000)	-598.4093 (0.0000)
ICE	-0.0891 (0.9842)	3.2868 (0.6296)	-14.5656 (0.1742)	3.5345 (0.6516)
DR	-3.9037 (0.0045)	-5.5972 (0.1671)	-6.2154 (0.1945)	-8.1248 (0.1348)
LMC	66.4429 (0.0000)	77.6094 (0.0000)	102.0463 (0.0000)	86.3122 (0.0000)
IND = Basic Industries	110.4627 (0.2019)	91.0761 (0.0845)	192.8343 (0.2077)	193.3949 (0.0019)
IND = Consumer Goods	286.1635 (0.0006)	229.6008 (0.0000)	354.1432 (0.0166)	342.8131 (0.0000)
IND = Consumer Services	87.0532 (0.2870)	65.7534 (0.2083)	183.4939 (0.2044)	132.0000 (0.0300)
IND = General Industrials	95.2374 (0.2234)	76.0997 (0.2083)	160.9223 (0.2431)	161.1541 (0.0045)
Adjusted R^2	0.2615 (0.0000)	0.3094 (0.0000)	0.1544 (0.0000)	0.2906 (0.0000)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 0.6252; P-value = 0.8650 Decision: Accept H_0: Pooled OLS Model **Hausman Test Chi-Sq. Statistic = 4.6821;** P-Value = 0.1966 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

The accepted model is again the random-firm-effects model. It is both statistically significant and has a moderate degree of explanatory power as indicated by the R^2. However, it is the role of LMC, alongside presence in the consumer goods industry, that plays the biggest role. This is indicated by the substantial βs alongside the statistical significance present for both factors.

The following table considers the role that ICE plays on MB.

Table 12: Results of Panel Regression of MB and ICE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 18:				
Intercept	-9.0003 (0.0266)	0.8568 (0.5426)	-20.01532 (0.3422)	-13.8456 (0.4733)
ICE	-0.3514 (0.0033)	-0.1561 (0.2751)	-1.1683 (0.5599)	-1.5099 (0.4183)
DR	-0.0388 (0.3114)	-0.0582 (0.7117)	-0.2300 (0.8575)	-0.2526 (0.8456)
LMC	1.4669 (0.0000)	-0.5993 (0.0000)	2.8419 (0.0666)	2.3267 (0.1060)
IND = Basic Industries	0.3678 (0.9381)	1.3326 (0.2162)	2.6828 (0.8719)	2.0349 (0.8905)
IND = Consumer Goods	1.8826 (0.6777)	1.1337 (0.2777)	4.8424 (0.7647)	3.5593 (0.8044)
IND = Consumer Services	6.7936 (0.1225)	2.0514 (0.0502)	22.9512 (0.1570)	21.0248 (0.1461)
IND = General Industrials	3.6559 (0.3881)	3.5339 (0.0003)	6.7990 (0.6534)	5.6375 (0.6753)
ROE	0.2506 (0.0000)	-0.0126 (0.6945)	0.3045 (0.4139)	0.3140 (0.4087)
Adjusted R^2	0.3682 (0.0000)	0.0915 (0.0000)	-0.0026 (0.6356)	-0.0023 (0.6117)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 1.8432; P-value = 0.0228 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model				

Hausman Test Chi-Sq. Statistic = 16.3139; P-Value = 0.0026 Decision: Reject H_0: Random Effects Model (Firm); thus accept H_1: Fixed Effects Model Hausman Test Chi-Sq. Statistic = 1.9399; P-Value = 0.9828 Decision: Accept H_0: Random Effects Model (Period)

The accepted models relating to MB are both fixed-firm-effects and random-period-effects as it was when considering VAIC. Similarly, the random effects model is not statistically significant and the fixed-effects is but has little explanatory power. ICE is not a statistically significant factor. Yet again when compared to Table 7, consumer service and general industrials have a notable and significant association of similar magnitude, however, interestingly ICE has almost the exact magnitude β compared to that of VAIC but with a negative association instead.

The following table evaluates the influence of ICE on TSR performance.

Table 13: Results of Panel Regression of TSR and ICE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 19:				
Intercept	0.3251 (0.0023)	0.2439 (0.0446)	1.5083 (0.1342)	1.6222 (0.0178)
ICE	-0.0123 (0.2267)	-0.0036 (0.7671)	-0.0293 (0.7324)	-0.0312 (0.6346)
DR	0.0088 (0.1308)	0.0067 (0.5708)	0.0070 (0.8755)	0.0040 (0.9303)
LMC	-0.0195 (0.0425)	0.0050 (0.5954)	-0.1352 (0.0524)	-0.1465 (0.0041)
IND = Basic Industries	0.1300 (0.0416)	0.1285 (0.1693)	-0.0350 (0.9674)	-0.0455 (0.9302)
IND = Consumer Goods	0.0569 (0.3384)	0.0945 (0.2951)	-0.2116 (0.7986)	-0.2332 (0.6444)
IND = Consumer Services	0.0212 (0.7321)	0.1036 (0.2517)	-0.3893 (0.6364)	-0.4327 (0.3946)
IND = General Industrials	0.1334 (0.0137)	0.2132 (0.0124)	0.4128 (0.5944)	0.3979 (0.4003)
ROE	0.0010 (0.7594)	0.0051 (0.7336)	0.0005 (0.9679)	-0.0022 (0.8707)
Adjusted R^2	0.0148 (0.0169)	0.0762 (0.0000)	-0.0026 (0.6343)	0.0093 (0.0670)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 4.3810; P-value = 0.0000 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 1.6304;** P-Value = 0.8033 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Chi-Sq. Statistic = 3.8117;** P-Value = 0.8737 **Decision: Accept H_0: Random Effects Model (Period)**				

From the above random effects for both firm and period are the appropriate models for analysis, however neither display a statistically significant relationship satisfying a 95% confidence interval nor effectively any explanatory power. It is noted that whilst a combined random-effects model would be ideal for complete evaluation, this is not possible as the panel under consideration is unbalanced and thus it is not computationally feasible.

4.5 CEE Panel Regression Results

The following tables display the consolidated results for equations 20-24 individually when applying the panel methods indicated in Figure 4. The first table again considers ROA but now accounting for the effect of CEE.

Table 14: Results of Panel Regression of ROA and CEE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 20:				
Intercept	0.0401 (0.0001)	0.0569 (0.0172)	-0.1076 (0.2099)	0.0169 (0.7515)
CEE	0.0147 (0.0343)	0.0061 (0.6261)	0.0398 (0.2440)	0.0462 (0.0990)
DR	-0.0005 (0.7141)	-0.0006 (0.8723)	0.0038 (0.2702)	-1.73E-05 (0.9963)
LMC	0.0046 (0.0000)	0.0034 (0.0809)	0.0182 (0.0021)	0.0045 (0.2736)
IND = Basic Industries	-0.0070 (0.4348)	-0.0039 (0.8384)	-0.0062 (0.9368)	-0.0169 (0.6938)
IND = Consumer Goods	0.0032 (0.6454)	-0.0019 (0.9155)	0.0338 (0.6518)	0.0105 (0.7991)
IND = Consumer Services	0.0345 (0.0000)	0.0305 (0.1005)	0.1215 (0.1027)	0.0720 (0.0851)
IND = General Industrials	0.0239 (0.0002)	0.0280 (0.0988)	0.0288 (0.6797)	0.0105 (0.7847)
Adjusted R^2	0.1024 (0.0000)	0.0285 (0.0061)	0.0117 (0.0311)	0.0111 (0.0362)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 1.8014; P-value = 0.0273 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 20.9787;** P-Value = 0.0001 **Decision: Reject H_0: Random Effects Model (Firm); thus accept H_1: Fixed Effects Model** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

The fixed-firm-effects model is the accepted correct method of panel analysis. It yields a statistically significant model with little explanatory power over all and no statistically significant relationships to any of the models explanatory variables.

The following table considers CEE's relationship with RG.

Table 15: Results of Panel Regression of RG and CEE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Cross-section weights)	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 21:				
Intercept	-0.0407 (0.5030)	0.0385 (0.5024)	-0.0286 (0.8956)	-0.0286 (0.8960)
CEE	0.0600 (0.0582)	0.0418 (0.1672)	0.1781 (0.1187)	0.1781 (0.1199)
DR	0.0046 (0.3735)	0.0033 (0.5306)	0.0051 (0.7364)	0.0051 (0.7373)
LMC	0.0086 (0.0706)	0.0089 (0.0054)	-0.0006 (0.9696)	-0.0006 (0.9697)
IND = Basic Industries	0.0919 (0.0606)	0.0771 (0.0962)	0.1280 (0.4655)	0.1280 (0.4670)
IND = Consumer Goods	0.0149 (0.7502)	0.0088 (0.8419)	0.1039 (0.5369)	0.1039 (0.5383)
IND = Consumer Services	0.0748 (0.1153)	0.0634 (0.1587)	0.1489 (0.3823)	0.1489 (0.3839)
IND = General Industrials	0.0576 (0.1853)	0.0514 (0.2104)	0.0554 (0.7227)	0.0554 (0.7236)
Adjusted R^2	0.0111 (0.0365)	0.0454 (0.0001)	-0.0040 (0.7669)	-0.0040 (0.7669)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 2.6584; P-value = 0.0004 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 6.5163;** P-Value = 0.0890 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

Based on the analysis the random-firm-effects model is the acceptable method however it displays no explanatory power and has no statistical significance.

The table below considers the performance of HEPS when accounting for the effect of CEE.

Table 16: Results of Panel Regression of HEPS and CEE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 22:				
Intercept	-393.7432 (0.0000)	-429.1772 (0.0000)	-721.7494 (0.0000)	-573.9899 (0.0000)
CEE	-21.9532 (0.2257)	-26.9421 (0.4432)	-20.6076 (0.6819)	-22.3388 (0.5841)
DR	-4.0853 (0.0029)	-5.9175 (0.1458)	-5.9018 (0.2184)	-8.4037 (0.1222)
LMC	66.6386 (0.0000)	78.4612 (0.0000)	102.4759 (0.0000)	86.8627 (0.0000)
IND = Basic Industries	107.0938 (0.2129)	85.3495 (0.1083)	195.0068 (0.2058)	187.0470 (0.0030)
IND = Consumer Goods	285.2207 (0.0006)	226.6879 (0.0000)	366.4058 (0.0135)	337.9846 (0.0000)
IND = Consumer Services	91.7414 (0.2583)	70.0874 (0.1814)	191.2531 (0.1882)	134.2363 (0.0279)
IND = General Industrials	98.1187 (0.2083)	74.9663 (0.2083)	180.5166 (0.1905)	157.7605 (0.0048)
Adjusted R^2	0.2627 (0.0000)	0.3101 (0.0000)	0.1523 (0.0000)	0.2907 (0.0000)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 0.5906; P-value = 0.8923 Decision: Accept H_0: Pooled OLS Model **Hausman Test Chi-Sq. Statistic = 2.9615;** P-Value = 0.3976 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Decision: Reject H_0: Random Effects Model (Period)**				

The random-firm-effects model is the accepted method however it does not indicate a statistically significant relationship to CEE but it is instead the effect of industry location, specifically consumer goods, and LMC that display significant associations as well as having large βs.

The following table considers MB against CEE.

Table 17: Results of Panel Regression of MB and CEE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 23:				
Intercept	-9.0674 (0.0334)	0.3672 (0.7910)	-30.7957 (0.1329)	-25.1824 (0.1740)
CEE	1.9476 (0.0099)	-0.1633 (0.8238)	12.2948 (0.2322)	12.9132 (0.1833)
DR	-0.0016 (0.9727)	-0.0561 (0.7188)	-0.1160 (0.9279)	-0.1173 (0.9276)
LMC	1.1402 (0.0000)	0.5872 (0.0000)	2.5855 (0.0973)	1.9383 (0.1749)
IND = Basic Industries	2.0203 (0.6772)	1.4020 (0.2064)	5.8523 (0.7273)	5.4449 (0.7148)
IND = Consumer Goods	2.8695 (0.5377)	1.3468 (0.2054)	6.8581 (0.6703)	5.7186 (0.6891)
IND = Consumer Services	5.8668 (0.1951)	2.1828 (0.0446)	21.6613 (0.1832)	19.3582 (0.1816)
IND = General Industrials	4.1201 (0.3441)	3.8295 (0.0001)	7.7454 (0.6046)	6.8416 (0.6061)
ROE	0.1689 (0.0000)	-0.0050 (0.8757)	0.2978 (0.6046)	0.3036 (0.4226)
Adjusted R^2	0.1883 (0.0000)	0.0855 (0.0000)	-0.0011 (0.5171)	-0.0010 (0.5049)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 1.8049; P-value = 0.0269 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model				

Hausman Test Chi-Sq. Statistic = 15.1627; P-Value = 0.0044 **Decision: Reject H_0: Random Effects Model (Firm); thus accept H_1: Fixed Effects Model** **Hausman Test Chi-Sq. Statistic = 5.8231;** P-Value = 0.6670 **Decision: Accept H_0: Random Effects Model (Period)**

The fixed-period-effects model is deemed the appropriate method based on the test results. This yields a statistically significant model of limited explanatory power, with CEE not playing a statistically significant role but instead presence in the general industrials sector and consumer service presence playing the significant roles and having magnitudes in descending order. The random effects model accounting for period effects was also acceptable however, displayed no statistical significance.

The final table below considers CEE's role in firm TSR.

Table 18: Results of Panel Regression of TSR and CEE with industry dummy variables

	Pooled OLS Method: Panel EGLS (Period SUR	Fixed Effects Model with period effects Method: Panel EGLS (Period weights)	Random Effects Model with firm effects Method: Panel EGLS (Swamy and Arora estimator of component variances)	Random Effects Model with period effects Method: Panel EGLS (Swamy and Arora estimator of component variances)
EQN 24:				
Intercept	0.2892 (0.2789)	0.2892 (0.2789)	0.9354 (0.3389)	1.3654 (0.0359)
CEE	0.2646 (0.0018)	-0.0072 (0.9080)	0.8348 (0.0464)	0.4640 (0.1733)
DR	0.0081 (0.2787)	0.0068 (0.5613)	0.0114 (0.7983)	0.0104 (0.8193)
LMC	-0.0310 (0.0760)	0.0051 (0.5927)	-0.1483 (0.0338)	-0.1668 (0.0009)
IND = Basic Industries	0.0768 (0.7581)	0.1267 (0.1776)	0.1605 (0.8519)	0.0642 (0.9024)
IND = Consumer Goods	-0.0618 (0.7963)	0.0940 (0.2947)	-0.1132 (0.8910)	-0.1903 (0.7047)
IND = Consumer Services	-0.1465 (0.5342)	0.1024 (0.2628)	-0.4747 (0.5648)	-0.5210 (0.3060)
IND = General Industrials	0.1753 (0.4307)	0.2160 (0.0098)	0.4189 (0.5855)	0.4020 (0.3885)
ROE	-0.0011 (0.4748)	0.0049 (0.7427)	0.0003 (0.8796)	-0.0008 (0.8502)
Adjusted R^2	0.0283 (0.0086)	0.0755 (0.0000)	0.0027 (0.2699)	0.0133 (0.0245)
Redundant Fixed Effects (Period) Likelihood Ratio Test F-Statistic = 4.3388; P-value = 0.0000 Decision: Reject H_0: Pooled OLS Model; thus accept H_1: Fixed Effects Model **Hausman Test Chi-Sq. Statistic = 4.3935;** P-Value = 0.3554 **Decision: Accept H_0: Random Effects Model (Firm)** **Hausman Test Period test variance is invalid. Hausman statistic set to zero. Reject H_0: Random Effects Model (Period)**				

From the above the random-firm-effects model is the acceptable one for consideration. However, the model possesses very little explanatory power and is not statistically significant.

Chapter 5. Discussion of Results

To simplify the consideration of the various variables' effect on financial performance, the discussions are grouped around the dependent variables results across all regressions rather than considering VAIC, ICE or CEE in isolation.

5.1 Financial Performance Implications

5.1.1 ROA Panel Regression Discussion

When considering any of the explanatory variables of interest, none of VAIC, ICE or CEE play a significant role when it comes to predicting ROA performance. This is contradictory to the findings of Morris (2015a) and Kongkiti et al. (2011) in South African and Thai contexts respectively but agrees with the findings of Maditinos et al. (2011) and Clarke et al. (2011) in the Australian context as well as in Indonesian manufacturing companies as found by Nuryaman (2015). It also doesn't support the strong positive association in Malaysia as noted by Ting and Lean (2009) or those for BRICS companies as determined by Nadeem et al. (2017).

Intuitively one would expect that there should be an association between intellectual capital and return on assets since it is the application of intellectual capital that drives the usage of productive assets. However, that rationale is not supported by the data and the study continues with the trend of historical studies of finding inconsistent results across both emerging markets and developed markets across a variety of industries.

Likewise, the efficiency with which capital is employed would also intuitively play a substantial role in ROA as it is likely that capital is utilised to secure the corresponding assets. Thus, efficient capital employment is indicative of good earnings performance and thus assets are likely to be productive. However, CEE doesn't appear to play a measurably significant role in the measurement of firm profitability as defined by ROA, therefore, anticipation or prediction using CEE as a tool is not supported by the study.

It is noted that it is possible that the individual structuring of companies in terms of asset value compared to operational activities would vary greatly and this is not incorporated into the current form of the analysis.

Furthermore, it is also possible that ROA is being influenced by impairments and acquisitions that greatly impact on the value but are difficult to control for in a practical sense within the model.

5.1.2 RG Panel Regression Discussion

As was observed with ROA, none of VAIC, ICE or CEE have statistically significant associations when it comes to firm growth as defined by revenue growth across industries or firms. This contradicts the findings of (Morris, 2015a) which found a positive association with HCE and RG, however, only for non-consumer driven industries in SA. It also contradicts the findings of (Chen et al., 2005) in Taiwan which found a positive association between intellectual capital and RG. Furthermore, (Kongkiti et al., 2011) found strong positive associations between intellectual capital and RG. Considering these three emerging markets one would expect that there may be similarities in the impact of intellectual capital however, the study does not support this when considering a broad range of industries and a relatively long time-horizon.

When considering revenue growth across industries, it is expected that the levels of growth across industries, regions and firms depending on the specific operating conditions will vary. Unfortunately, based on the above results employee value add as defined by VAIC and ICE contribution to revenue growth cannot be used as a predictive tool across these various operating conditions in the South African context. The validity of CEE as a predictive tool broadly speaking with relation to RG would be questionable in any event as its applicability would be heavily tied to the nature of specific firms' level of dependence on capital to drive revenue generation and the individual firms' operational structures.

5.1.3 HEPS Panel Regression Discussion

The final financial performance metric under consideration is that of HEPS. It would be expected that earnings would be related to the value added by employees, as measured by ICE, and capital, as measured by CEE and correspondingly their combined result of VAIC but again the study does not support this outcome for any of the three variables. This is in contradiction to (Morris, 2015a) which found a positive and significant correlation for all industries and intellectual capital, as measured by HCE, with the exception of the Technology industry. However, since neither RG nor ROA displayed any relationship to VAIC it is not surprising that another earnings, or revenue, driven metric continues this trend.

5.2 Market Performance Implications

5.2.1 MB and TSR Panel Regressions Discussion

Based on historical studies market valuation has yielded far fewer conclusive results in comparison to financial performance indicators such as ROA. Specifically, Firer and Stainbank (2003), Firer and Williams (2003) and Morris (2015a) in South Africa and Maditinos et al. (2011) in Greece all found no statistically significant evidence of an association between market performance and intellectual capital. The exceptions to this rule, not exhaustively, are Chen et al. (2005) in Taiwan and Nuryaman (2015) in Indonesia who found strong positive associations between MB and intellectual capital. Morris (2015a) likewise found no statistically significant results between intellectual capital and TSR.

When it comes to market performance it is anticipated that value added by intellectual capital would not necessarily have an impact on share price performance since numerous other factors, completely unrelated to the core operational ability of the company, can play a significant role. These include, to name but a few, the prevailing economic conditions, the stage of the business cycle, foreign exchange effects, the relevant industry's holistic difficulties, as well as individual firms' perceptions in the market and media. The collective effect of these market sentiment factors impact both on firms' perceived value, in the form of share price and thus market capitalisation, and the appetite of investors to expose themselves to local equity risks. This is typically deemed to have a substantially greater impact than the effect of intellectual capital and by and large the aforementioned historical studies, along with the findings of this study, support this fact.

Chapter 6. Conclusion

It is indisputable that as the knowledge economy grows and the Fourth Industrial Revolution takes a firmer hold, the importance of intellectual capital, in the form of skilled application of knowledge work, will represent ever greater importance. Despite this intuitively logical conclusion however, accurate capturing of the true value of intellectual capital and human capital, as well its measurable impact, remains elusive. This is evidenced by the lack of any significant relationships found by the overall and component portions of the VAIC model when compared to fairly standard market and financial performance metrics, specifically ROA, RG, HEPS, MB ratio and TSR. The study has not indicated any further conclusive insights within South Africa into intellectual capital effect as defined by VAIC despite accounting for Firer and Williams (2003) stated research limitations and extending the study of Morris (2015a) to include the complete VAIC model and over a longer period of 17 years compared to 10 years. Furthermore, the study doesn't support the findings of Morris (2015a) despite evaluating the same period for more direct comparison. However, it is noted that due to the data collection and exclusion method the sample size, from a cross-sectional perspective, for this study is significantly less than that of Morris (2015a).

Just as much of knowledge work remains tacit and difficult to quantify, drawing meaningful insights using traditional performance metrics with respect to intellectual capital is difficult to do using explicit, quantitative data. This could have multiple causes such as, the VAIC model potentially being inadequate as a proxy for a quantitative measure of intellectual capital, intellectual capital may not have a direct relationship with firm performance, or it may not have one in the current South African operational environment.

The net effect is that there are limited implications for management to draw from with intellectual capital measurement in the presented form when compared to traditional performance measures and more research would be required to provide a method to provide investors and management the necessary insights to evaluate and anticipate firm performance in a South African context when considering the role of intellectual capital.

Chapter 7. Recommendations for future research

To establish a meaningful method to evaluate the effect of intellectual capital on firm performance, the following recommendations are provided.

A factor that hasn't been accounted for when compared to the study of Morris (2015a) is the role played by the prevailing South African economy due to the spiralling effects of State Capture and its structural economic issues such as unemployment. To allow for more direct comparison, the study could be split up between 2001-2011 and 2012-2017 as well as collectively, to validate the results of Morris (2015a) over the same period including and subsequently evaluate the years following her study.

Alternatively, the study could be expanded by relaxing the data selection and exclusion criteria to include all companies listed for the period as well as those that don't report all required figures for the targeted period amount of 12 years, however it is noted that substantially greater data cleaning exercises may be required if this is performed.

REFERENCES

Alhassan, A. L., & Asare, N. (2016). Intellectual capital and bank productivity in emerging markets: evidence from Ghana. *Management Decision, 54*(3), 589-609. doi:doi:10.1108/MD-01-2015-0025

Brooks, C. (2008). *Introductory Econometrics for Finance* (2nd ed.). United States of America: Cambridge University Press.

Chen, M. C., Cheng, S. J., & Hwang, Y. (2005). An empirical investigation of the relationship between intellectual capital and firms' market value and financial performance. *Journal of Intellectual Capital, 6*(2), 159-176. doi:doi:10.1108/14691930510592771

Clarke, M., Seng, D., & Whiting, R. H. (2011). Intellectual capital and firm performance in Australia. *Journal of Intellectual Capital, 12*(4), 505-530. doi:doi:10.1108/14691931111181706

Cronje, C. J., & Moolman, S. (2013). Intellectual capital : measurement, recognition and reporting. *South African Journal of Economic and Management Sciences, 16*(1), 1-12.

De Jager, P. (2008). Panel data techniques and accounting research. *Meditari : Research Journal of the School of Accounting Sciences, 16*(2), 53-68.

European Commission. (2014a, 23 August 2017). Coding - the 21st century skill. Retrieved from https://ec.europa.eu/digital-single-market/en/coding-21st-century-skill

European Commission. (2014b, 26 February 2018). The Digital Skills and Jobs Coalition. Retrieved from https://ec.europa.eu/digital-single-market/en/digital-skills-jobs-coalition

European Commission. (2018). *Capitalising on the benefits of Research & Innovation Projects for Policy The 4th Industrial Revolution* Retrieved from https://ec.europa.eu/info/sites/info/files/4threvolution_p4p-report_2017.pdf

European Political Strategy Centre. (2016). The Future of Work Skills and Resilience for a World of Change. In E. Commission (Ed.), *EPSC Strategic Notes* (Vol. 13): European Political Strategy Centre,.

Firer, S. (2005). Using intellectual capital as a success strategy in South Africa : research article. *Southern African Business Review, 9*(1), 1-20.

Firer, S., & Stainbank, L. (2003). Testing the relationship between intellectual capital and a company's performance: Evidence from South Africa. *Meditari Accountancy Research, 11*(1), 25-44. doi:doi:10.1108/10222529200300003

Firer, S., & Williams, M. S. (2003). Intellectual capital and traditional measures of corporate performance. *Journal of Intellectual Capital, 4*(3), 348-360. doi:doi:10.1108/14691930310487806

Ghosh, S. K., & Maji, S. G. (2015). Empirical Validity of Value Added Intellectual Coefficient Model in Indian Knowledge-based Sector. *Global Business Review, 16*(6), 947-962.

IASB. (2011). International Financial Reporting Standards (IFRSs). 2011: including International Accounting

Standards (IASs) and Interpretations. In (Vol. Vol 1A). London.

IHS Markit. (2017a). *Eviews 10 User's Guide I* (2nd ed.): IHS Markit.

IHS Markit. (2017b). *Eviews 10 User's Guide II* (2nd ed.): IHS Markit.

International Automotive Task Force. (2016). IATF 16949:2016. In: IATF.

Jonker, M. (2015). South African business slow to embrace automation. *International Business Report.* Retrieved from https://www.grantthornton.co.za/insights/articles/south-african-business-slow-to-embrace-automation/

Joshi, M., Cahill, D., Sidhu, J., & Kansal, M. (2013). Intellectual capital and financial performance: an evaluation of the Australian financial sector. *Journal of Intellectual Capital, 14*(2), 264-285. doi:doi:10.1108/14691931311323887

JSE. (2010). JSE Limited Listings Requirements. In: LexisNexis.

Kalkan, A., Bozkurt, Ö. Ç., & Arman, M. (2014). The Impacts of Intellectual Capital, Innovation and Organizational Strategy on Firm Performance. *Procedia - Social and Behavioral Sciences, 150*, 700-707. doi:https://doi.org/10.1016/j.sbspro.2014.09.025

Kongkiti, P., Narongsak, C., Agnieszka, S. L., & Keng-Boon, O. (2011). Interrelationships between intellectual capital and performance: Empirical examination. *Industrial Management & Data Systems, 111*(6), 810-829. doi:doi:10.1108/02635571111144928

Maditinos, D., Chatzoudes, D., Tsairidis, C., & Theriou, G. (2011). The impact of intellectual capital on firms' market value and financial performance. *Journal of Intellectual Capital, 12*(1), 132-151. doi:doi:10.1108/14691931111097944

McDowell, W. C., Peake, W. O., Coder, L., & Harris, M. L. (2018). Building small firm performance through intellectual capital development: Exploring innovation as the “black box”. *Journal of Business Research, 88*, 321-327. doi:https://doi.org/10.1016/j.jbusres.2018.01.025

Meles, A., Porzio, C., Sampagnaro, G., & Verdoliva, V. (2016). The impact of the intellectual capital efficiency on commercial banks performance: Evidence from the US. *Journal of Multinational Financial Management, 36*, 64-74. doi:https://doi.org/10.1016/j.mulfin.2016.04.003

Molele, M. H. (2018). *Foreign Exchange Risk Exposure, Hedging Behaviour, and Corporate Valuations: Evidence from South Africa.* (Doctor of Philosophy), University of Cape Town, Cape Town.

Molodchik, M., & Bykova, A. (2011). Applying the VAIC Model to Russian Industrial Enterprises. *Proceedings of the European Conference on Intellectual Capital*, 268-277.

Morris, C. (2015a). An industry analysis of the power of human capital for corporate performance : evidence from South Africa. *South African Journal of Economic and Management Sciences, 18*(4), 487-499. doi:doi:http://dx.doi.org/10.17159/2222-3436/2015/v18n4a4

Morris, C. (2015b). Developments in the value-added efficiency of South African workers - an exploratory study. *South African Journal of Business Management, 46*(4), 35-42.

Nadeem, M., Gan, C., & Nguyen, C. (2017). Does intellectual capital efficiency improve firm performance in BRICS economies? A dynamic panel estimation. *Measuring Business Excellence, 21*(1), 65-85. doi:doi:10.1108/MBE-12-2015-0055

Nuryaman. (2015). The Influence of Intellectual Capital on The Firm's Value with The Financial Performance as Intervening Variable. *Procedia - Social and Behavioral Sciences, 211*, 292-298. doi:https://doi.org/10.1016/j.sbspro.2015.11.037

OECD, O. f. E. C.-o. a. D. (1999). *Guidelines and instructions for OECD Symposium*. Paper presented at the International Symposium Measuring Reporting Intellectual Capital: Experiences, Issues, and Prospects, Amsterdam, OECD.

Petty, R., & Guthrie, J. (2000). Intellectual capital literature review: Measurement, reporting and management. *Journal of Intellectual Capital, 1*(2), 155-176. doi:doi:10.1108/14691930010348731

Pulic, A. (2000). VAIC--an accounting tool for IC management. *International Journal of Technology Management, 20*(5-8), 702.

Pulic, A. (2004). Intellectual capital – does it create or destroy value? *Measuring Business Excellence, 8*(1), 62-68. doi:doi:10.1108/13683040410524757

PwC South Africa. (2011). Audit and accounting requirements of the new Companies Act. In: PwC South Africa.

Sardo, F., Serrasqueiro, Z., & Alves, H. (2018). On the relationship between intellectual capital and financial performance: A panel data analysis on SME hotels. *International Journal of Hospitality Management, 75*, 67-74. doi:https://doi.org/10.1016/j.ijhm.2018.03.001

South African Reserve Bank. (2018). Online statistical query (historical macroeconomic timeseries information) - Labour Productivity 1970-2016. Retrieved from https://www.resbank.co.za/Publications/QuarterlyBulletins/Pages/QBOnlinestatsquery.aspx

Ståhle, P., Ståhle, S., & Aho, S. (2011). Value added intellectual coefficient (VAIC): a critical analysis. *Journal of Intellectual Capital, 12*(4), 531-551. doi:doi:10.1108/14691931111181715

Startz, R. (2015). *Eviews Illustrated for Version 9* (M. Startz & I. G. Inc. Eds.).

Stats SA. (2014, 20 September 2014). Employment, unemployment, skills and economic growth. Retrieved from https://www.statssa.gov.za/presentation/Stats%20SA%20presentation%20on%20skills%20and%20unemployment_16%20September.pdf

The Banking Association of South Africa. (2018). SME Enterprise. Retrieved from http://www.banking.org.za/what-we-do/sme/sme-enterprise

The World Bank. (2018a). GDP growth (annual %) - South Africa. Retrieved from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2017&locations=ZA&start=2001&view=chart

The World Bank. (2018b). GDP per person employed (constant 2011 PPP $). Retrieved from https://data.worldbank.org/indicator/SL.GDP.PCAP.EM.KD?contextual=default&locations=ZA-1W-EU-US-ZG

The World Bank. (2018c). Inflation, consumer prices (annual %) - South Africa. Retrieved from https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?end=2016&locations=ZA&start=1960&view=chart&year_low_desc=false

Ting, I. W. K., & Lean, H. H. (2009). Intellectual capital performance of financial institutions in Malaysia. *Journal of Intellectual Capital, 10*(4), 588-599. doi:doi:10.1108/14691930910996661

Todericiu, R., & Stăniţ, A. (2015). Intellectual Capital – The Key for Sustainable Competitive Advantage for the SME's Sector. *Procedia Economics and Finance, 27*, 676-681. doi:https://doi.org/10.1016/S2212-5671(15)01048-5

Wagiciengo, M. M., & Belal, A. R. (2012). Intellectual capital disclosures by South African companies: A longitudinal investigation. *Advances in Accounting, 28*(1), 111-119. doi:https://doi.org/10.1016/j.adiac.2012.03.004

Wits Business School. (2017). Validity & Reliability. In. Wits Business School.

World Economic Forum. (2016). *The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution - Executive Summary*. Retrieved from Geneva, Switzerland:

Zumbrun, J. (2016). The Rise of Knowledge Workers Is Accelerating Despite the Threat of Automation. Retrieved from https://blogs.wsj.com/economics/2016/05/04/the-rise-of-knowledge-workers-is-accelerating-despite-the-threat-of-automation/