The relationship between VAIC™, firm performance and firm value of companies: A Cross-Country Analysis

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DECLARATION

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I dedicate this dissertation to my wife, Astrid. Thank you for your patience, unconditional love and unwavering support throughout this journey. Thank you cannot describe the appreciation I have for what you have had to endure over the past three years. Love you, Darling.

To my parents, this is for you! Thank you that you always believe and want me to do better. I appreciate you.

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ABSTRACT

Purpose – The aim of this research was to examine the relationship between intellectual capital (IC), firm performance and firm value in South Africa, Brazil and Indonesia.

Design/Methodology/Approach – The study applied the difference generalised method of moments (DGMM) estimator to investigate the relationship between 787 listed firms from the Johannesburg Stock Exchange (JSE), the Brazil Stock Exchange (B3.S.A) and the Indonesia Stock Exchange (BEI), spanning 5 years from 2019–2023 making use of the VAIC™ approach and its components to test the relationship with firm performance and firm value. The study used secondary data from Eikon Refinitiv.

Findings – The study found that firms in all three countries leverage both intangible and physical capital at a composite level (VAIC™) to enhance performance. However, from a valuation perspective, the market only reward firms in Brazil at an aggregate level. The individual VAIC™ components show mixed results across the countries. Brazilian and Indonesian enterprises appear to utilise their human and physical capital more efficiently to generate shareholder returns and create value compared to South African companies. In contrast, South African firms tend to invest in innovation—such as patents, trademarks, systems, and processes—to achieve positive returns, even though this may the stifle shareholder wealth creation.

Practical Implications – In general, physical capital dominates the findings. It suggests that the market continues to reward firms for using this source of capital to generate shareholder wealth. The findings imply SCE and HCE offer limited value on their own and that it benefits firms to use both intangible and tangible assets.

Originality/Value – The study builds on the research of Nadeem et al. (2017) and Nadeem et al. (2019) by providing an updated analysis utilising the DGMM. There is a dearth of studies that have adopted the DGMM to investigate the relationship of IC with firm performance and firm value on a cross-country basis on South Africa, Indonesia and Brazil. Given the limited research using this particular method of the GMM, we are contributing to filling this void.

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4IR	4th Industrial Revolution
ADF	Augmented Dickey-Fuller
ANOVA	Analysis of Variance
AR (1)	First-order Autoregression
AR (2)	Second-order Autoregression
ASEAN	The Association of Southeast Asian Nations
ATO	Asset Turnover
B3.S.A	Brasil, Bolsa, Balcão
BEI	Bursa Efek Indonesia
BLUE	Best Linear Unbiased Estimate
BP	Breusch-Pagan
BRICS	Countries of Brazil, Russia, India, China and South Africa
BSC	Balanced Score Card
CEE	Capital Employed Efficiency
DGMM	Difference Generalised Method of Moments
EP	Employee Productivity
EVA™	Economic Value Added
FE	Fixed Effects
GDP	Gross Domestic Product
GKI	Global Knowledge Index
GMM	Generalised Method of Moments
HCE	Human Capital Efficiency
IAM	Intangible Asset Monitor
IC	Intellectual Capital
ICE	Intellectual Capital Efficiency
IQR	Inter-Quartile Range

IV	Instrumental Variable
JSE	Johannesburg Stock Exchange
k	Invested Capital/Capital Employed
KBE	Knowledge Based Economy
Lev_ratio	Leverage Ratio
MB	Market-to-Book Ratio
mVAIC™	Modified Value Added Intellectual Capital
NOPAT	Net Operating Profit After Tax
OI/S	Operating Income over Sales
OLS	Ordinary Least Squares
R&D	Research and Development
RC	Relational Capital
RCE	Relational Capital Efficiency
RG	Revenue Growth
ROA	Return on Assets
ROAA	Return on Average Assets
ROAE	Return on Average Equity
SADC	South African Development Community
SCE	Structural Capital Efficiency
SME	Small and Medium-Size Enterprises
UK	United Kingdom
USA	United States of America
VA	Value Added
VAIC™	Value Added Intellectual Capital
VIF	Variance Inflation Factor
W	Wooldridge
WACC	Weighted Average Cost of Capital

CHAPTER 1: INTRODUCTION

1.1 Introduction

Numerous academics agree that the knowledge-based economy (KBE) has become very important in our transition to a digitised, technology-driven and globalised competitive landscape where intellectual capital (IC), a subset of intangible assets, has become a significant component in value creation (Sveiby, 1997b; Pulic, 2004; Marr et al., 2004; Śledzik, 2013; Schwab and Zahidi, 2020; Azamat et al., 2023). Moreover, in support of value creation, Pulic (2004) states that IC must be treated as an investment instead of an expense.

According to Bamel et al. (2022), in pursuit of understanding the reasons behind the IC phenomena, many journal articles have been published on the topic. Academics have furthermore been interested in understanding the relationship between IC, firm performance, and firm value (Firer and Williams, 2003; Nadeem et al., 2017; Bhattu-Babajee and Seetanah, 2022). Moreover, transitioning to a knowledge-based economy, researchers note a divergence between the market and the net asset values of firms, which is said to be reflective of the "hidden assets" that are not encapsulated in financial statements (Roos and Roos, 1997; Sveiby, 1997a; Edvinsson et al., 2022). According to Maji and Goswami (2016) and Nadeem et al. (2017), accounting standards have failed to explain this phenomenon.

Numerous studies across the developed and emerging markets have focused on Value Added Intellectual Coefficient (VAIC™) (Pulic, 2000) or an adjusted/modified/extended variation of the same (Nimtrakoon, 2015; Soetanto and Liem, 2019; Xu and Li, 2022; Nadeem et al., 2019). Additionally, researchers attempted to understand the statistical significance and direction of the components of the VAIC™ index, namely human capital, structural capital, relational capital, and capital employed. However, the results over the past two decades have been inconclusive (Smriti and Das, 2018; Xu and Liu, 2020), although Chen et al. (2005), Clarke et al. (2011), Nadeem et al. (2018), and Bhattu-Babajee and Seetanah (2022) found a statistically significant positive relationship between VAIC™, its components, firm performance, and firm value.

In the context of emerging markets and explicitly looking across two or more countries, Nimtrakoon (2015) and Nadeem et al. (2017) found a positive and statistically significant relationship with mVAIC/VAIC™ across ASEAN and BRICS countries. However, comparatively, the results of the mVAIC™ and VAIC™ components differed. Whilst Nadeem et al. (2017) found statistically positive results, Nimtrakoon (2015) found mixed outcomes. For example, Nimtrakoon (2015) demonstrated positive human capital and capital-employed efficiencies associated with the dependent variables. Moreover, Nimtrakoon (2015) suggests

that the relationship between structural capital and relational capital efficiency with its dependent variables, apart from firm value, is statistically insignificant. In contrast, Nadeem et al. (2017) demonstrated a positive relationship between the VAIC™ components and the dependent variables. Olarewaju and Msomi (2021) studied VAIC™ and its components by looking at the insurance industry within the SADC region. Olarewaju and Msomi (2021) reported a statistically positive relationship between the dependent and independent variables of human capital, structural capital, and VAIC™ but a statistically negative relationship with capital employed. These studies and their associated results will be unpacked in Chapter Two.

To improve competitiveness, South African companies understand that human capital and infrastructure (financial and physical capital) is critical to the transition of the 4th Industrial Revolution (4IR) and to position South Africa for economic growth (National Planning Commission, 2013; Teixeira and Queirós, 2016; Bayode et al., 2019). According to the 2023 Global Knowledge Index (GKI) published by the United Nations Development Programme and others, which "measures the knowledge performance of countries…" (GKI, 2023), South Africa ranked 51st out of 133 countries for research and development (R&D) and innovation. The absolute score was marginally better than the global average. Additionally, South Africa performed better than its BRICS counterparts, although China did not form part of this index. The question remains whether this result has and will position South Africa on a path of value creation. Therefore, understanding the impact of IC on value creation is paramount. Against this backdrop, we also need to know how South Africa compares to other emerging market economies.

1.2 Problem Statement

South Africa is the most industrialised country on the African continent (Morris, 2015; Quaynor et al., 2022). Given this status and its current economic performance in the wake of low GDP growth, high levels of unemployment, and unskilled labour (UNDP, 2022) it is important for South African companies to understand how IC, represented by human capital and structural capital contributes towards value creation and firm performance. Human capital is a fundamental catalyst for firm performance, technological advancement, and innovation (Morris, 2015).

The research on intellectual capital (IC) and its influence on firm performance has focused on analysing single countries. With some exceptions (e.g. Nimtrakoon, 2015; Nadeem, 2016; Nadeem et al. 2017; Sardo and Serrasqueiro, 2018), these studies have been limited by small sample sizes and constrained data availability. Additionally, the studies in certain instances only focused on IC-intensive or single sectors of the economy, thus precluding other sectors where IC can also be impactful (Firer and Mitchell Williams, 2003). Consequently, the

generalisation of these findings is challenging. Whilst the impact of IC on firm performance and market value has been widely researched for countries on a standalone basis, studies of cross-country emerging market economies have been limited (Nimtrakoon, 2015; Nadeem et al., 2017; Maluleke, 2020; Olarewaju and Msomi, 2021). This is a gap in literature that this study aims to address. Its focus is on understanding the impact and the relationship between IC, firm performance and firm value of South African companies compared to other emerging market economies.

1.3 Research Aim and Objectives

The study aims to examine the relationship between intellectual capital, firm performance and firm value by making use of VAIC™ (Pulic, 2000) and accounting metrics (Chen et al., 2005; Nimtrakoon, 2015; Nadeem et al., 2017) by taking a look at the three emerging market countries, namely South Africa, Indonesia and Brazil. The research attempts to achieve the following objectives:

- To determine the relationship between VAIC™ and firm performance
- To determine the relationship between VAIC™ and firm market value
- To determine the relationship between the components of IC and firm performance
- To determine the relationship between the components of IC and firm market value
- In each of the instances above, to compare the outcome for South African firms with that of the other countries included in the study.

1.4 Research Questions

Given the aforementioned, our formulated research questions are the following:

- What is the relationship between VAIC™ and the firm's performance in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between VAIC™ and the firm's market value in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between the components of IC and the firm's performance in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between the components of IC and the firm's market value in emerging market countries of South Africa, Indonesia, and Brazil?

1.5 Research Hypotheses

To achieve the objectives and answer the research questions of the study, hypotheses will be formulated to test VAIC™, its components and the relationship with firm performance and firm

market value based on prior studies (Nimtrakoon, 2015; Nadeem et al., 2017; Sardo et al., 2018; Olarewaju and Msomi, 2021).

- $H_{1(a)}$ = HCE has a positive relationship with the return-on-assets ratio.
- $H_{1(b)}$ = HCE has a positive relationship with the asset-turnover ratio.
- $H_{1(c)}$ = HCE has a positive relationship with market value-to-book value ratio.

- $H_{2(a)}$ = SCE has a positive relationship with the return-on-assets ratio.
- $H_{2(b)}$ = SCE has a positive relationship with the asset-turnover ratio.
- $H_{2(c)}$ = SCE has a positive relationship with the market value-to-book value ratio.

- $H_{3(a)}$ = CEE has a positive relationship with the return-on-assets ratio.
- $H_{3(b)}$ = CEE has a positive relationship with the asset-turnover ratio.
- $H_{3(c)}$ = CEE has a positive relationship with the market value-to-book value ratio.

- $H_{4(a)}$ = VAIC™ has a positive relationship with the return-on-assets ratio.
- $H_{4(b)}$ = VAIC™ has a positive relationship with the asset-turnover ratio.
- $H_{4(c)}$ = VAIC™ has a positive relationship with the market value-to-book value ratio.

1.6 Rationale and Significance

The study contributes by building on the existing body of literature and filling the void by empirically examining the relationship between IC, firm performance and firm market value by conducting a cross-country analysis and comparing South Africa to the emerging market countries, namely Indonesia and Brazil. According to the Global Innovation Index report (World Intellectual Property Organisation, 2023), the aforementioned countries are “innovation overperformers”.

The Global Innovation Index report postulates that the ability of these countries to innovate is at a level superior to what is expected relative to their economic development (World Intellectual Property Organisation, 2023). Hence, these countries form part of the study. It is important to understand how intellectual capital impacts various socio-political and economic settings. Moreover, considering that human capital is the catalyst for innovation, it is apt to consider the aforementioned (Morris, 2015). Furthermore, Firer and Mitchell Williams (2003) argue that emerging markets are crucial in global wealth creation.

Published research comparing South Africa from a cross-country perspective has been scarce and inconclusive in determining the association between IC, VAIC™, firm performance and firm value from a cross-country perspective in emerging markets. Therefore, it is warranted to review the same and establish if there is indeed a relationship.

This cross-country study is expected to support the idea that IC in emerging markets contributes positively to firm performance and firm value. Thus, the study will contribute to existing knowledge that suggests IC is a hidden value creator (Sullivan, 1999; Roos and Roos, 1997). Moreover, we expect the study to support the hypothesis behind VAIC™ and its components (Pulic, 2004) and IC as value creator (Stewart, 1997; Edvinsson, 1997).

Understanding the relationship between IC, firm performance and firm value may provide better insight into government and business policy and operational, financial, and strategic decision-making, which may enhance shareholder and broader stakeholder value.

1.7 Theoretical Foundation

Literature suggests that intangible assets, such as employee expertise, organisational systems, and customer relationships, are critical drivers of sustainable competitive advantage. It suggests further that intellectual capital, comprising human, structural, and relational capital, enhances a firm's capacity to innovate, adapt, and build strong stakeholder networks. These views define a resource-based (Kamaluddin and Rahman, 2013) and a knowledge-based (Kengatharan, 2019) view of the relationship between intellectual capital and firm value. Finally, literature suggests that high levels of intellectual (Caputo et al., 2016) capital can serve as a positive signal to investors and the market, influencing perceptions of future performance and, consequently, firm valuation. This is generally referred to as signaling theory (Caputo et al., 2016). These generally accepted relationships form the theoretical basis for this study.

1.8 Delimitations of the study

The study is sector and market capitalisation agnostic. In other words, the study includes all industry and firm size. Companies with gaps in the data set were excluded from the study resulting in a balanced panel data spanning from 2019 – 2023. Consequently, the study only considered actively trading enterprises with complete data. The study uses the VAIC™ model and its components to test the hypotheses. It does not account for the extended and modified variations available in research as it is not the intent to pass judgement on the model but to garner insight from the data and models.

1.9 Limitations of the study

The VAIC™ model does not account for relational capital or innovation capital due to lack of data availability (Nimtrakoon, 2015; Nadeem et al., 2019). Given the approach to balanced

panel data set and exclusion of enterprises that did not report salaries and wages, the study is exposed to survivorship bias which could subject the models to incorrect inferences. Furthermore, during the period under consideration, the novel COVID-19 virus broke out worldwide and adversely impacted the trading of firms. This study did not account for this particular crisis; thus, the models could suffer from omitted variables.

1.10 Outline of the Study

The rest of the dissertation is outlined as follows. Chapter 2 introduces the literature review and sets the scene for what is to follow. The first part of the literature review discusses the definitions and models of IC and its components in detail. Thereafter, the study considers the various applicable scholarly articles published within the IC realm in the context of the developed and emerging markets. The literature review section closes off with a summary of the covered content.

Chapter 3 discusses the research methodology, design, and population. The report also considers the applicable variables, data and collection methods, and how the data will be analysed through the various diagnostic tests. The section rounds with off a summary.

In the final two chapters, a presentation and analysis of the results, a discussion of the results, and conclusions with recommendations for future research are articulated in Chapters 4 and 5, respectively.

1.11 Summary and Conclusion

Chapter 1 provides an overview of the dissertation's scope by delineating the significant literature that underpins IC. The author outlines the research hypotheses and objectives, which serve as guiding principles for the study. In Chapter 2, a deeper exploration of the literature that forms the framework for this study sets the stage for the subsequent sections of the research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Chapter 2 provides an overview and definition of IC. We proceed to unpack the components of IC in greater detail including the various valuation models. We conclude the chapter with an assessment of how empirical research of IC has shaped the landscape from a developed and emerging market perspective, its relationship with firm performance as well as firm value. The chapter ends with a summary.

2.2 Defining Intellectual Capital

The concept of Intellectual Capital (IC) has been around for over three decades, leading to various definitions of the discipline. Stewart (1997:ix) described IC as the "sum of everything everybody in a company knows that gives it a competitive edge." This implies that IC is based on the idea that knowledge provides a competitive advantage. IC is considered an intangible asset that does not follow traditional accounting rules and is a non-monetary asset with benefits in subsequent years.

The concept of IC has gained increased attention, leading to various definitions based on the role, components, and perspectives. For instance, Roos and Roos (1997) define IC as the unseen or "hidden" assets not fully recognised in a business's balance sheet. Sullivan (1999) suggests that IC is knowledge that translates into earnings or, in other words, knowledge that creates value.

Marr and Moustaghfir (2005) propose that IC can be defined by three main categories: strategic management, influencing behaviour, and external validation. Similarly, Sveiby (1997b) suggests that IC can be categorised into three parts: employee competence, internal structure, and external structure.

These researchers have different views on what IC includes. Bontis (1998) argues that IC does not encompass intellectual property, such as copyrights and patents. This contradicts Brooking's (1996) definition, which includes intellectual property as part of IC. Additionally, Petty and Guthrie (2000) argue that a firm's reputation is not part of IC and can be seen as a by-product of using IC.

There are various categorisations of IC (Choong, 2008), but it can be summarised into three components: human capital, structural capital, and relational capital. These components form the basis for this research and underpin VAIC™ as per Pulic (2000).

2.3 Components of Intellectual Capital

The components of intellectual capital (IC), including human capital, structural capital, and relational capital, have been extensively studied by researchers for their relationship to various dependent variables (Nimtrakoon, 2015; Sardo et al., 2018; Sowaity, 2022; Xu and Liu, 2020). Stewart (1997) emphasises their importance, stating that intangible assets, such as employee abilities (human capital), system efficiency (structural capital), and relationships with customers and suppliers (relational capital), contribute more to a knowledge-driven company's value than tangible assets.

Stewart and Ruckdeschel (1998) define human capital as employees' ability to innovate and meet client needs. Bontis (1998) describes human capital at an individual level as being based on genetic ability, education, experience, and attitude. According to Roos and Roos (1997), human capital is the knowledge in employees' heads, making it unpredictable. Edvinsson (1997) and Bontis (2001) argue that firms rent employee outputs and cannot own them, as employees may leave. What remains is structural capital, the tools of the trade.

The assets and resources owned by a business, known as structural capital, can be utilised to create value for shareholders and remain with the company even after an employee leaves (Bontis, 2001). Unlike human capital, Edvinsson (1997) argues that structural capital can be owned, bought, and sold by the firm. It includes hardware, software, databases, organisational structure, patents, trademarks, and everything else related to organisational capability (Bontis, 2001). This can be beneficial for financing, as the company can leverage it.

External capital can be categorised as relational capital (Petty and Guthrie, 2000), referring to the relationships with suppliers and customers (Stewart, 1997; Bontis, 1998). It is considered a key component of intellectual capital, akin to brand names, trademarks, and the company's reputation (Sveiby, 1997b). Relational capital turns intellectual capital into revenue, measured not only in hard currency but also through brand value or equity (Stewart, 1997).

2.4 Intellectual Capital Valuation Models

According to Ståhle et al. (2011) as well as Petty and Guthrie (2000), several models have been developed to measure and manage intellectual capital. Still, they have not demonstrated its economic impact (Nadeem et al., 2019). Sveiby (2010) suggests at least forty-two different models, falling into four approaches. This review will focus on the most important models.

According to Sveiby (2010) and Edvinsson (1997), the **Skandia Navigator™** model was developed to include non-financial information in the form of human and structural capital as key components of Intellectual Capital (IC). Bontis (2001) suggests that the model encompasses five key areas and comprises 164 metrics to measure these areas. However, it

has strengths in recognising the importance of customer capital but also drawbacks, as it requires an understanding of the drivers of intangible assets and could lead to biases. Pulic (1998) suggests that the model provides only a static balance sheet view, lacking representation of dynamic organizational flows.

The **Balanced Scorecard (BSC)** by Kaplan and Norton (1993) has four perspectives: financial, customer, processes, and learning and growth. It aligns a company's mission and strategy and focuses on both financial and non-financial metrics. However, it is not a one-size-fits-all tool and requires frequent assessments against performance metrics, which can overshadow strategic imperatives. As with the Skandia Navigator™, the BSC cannot be used for comparison purposes given the bespoke nature of the model which is also rooted in bias (Sveiby, 1997b).

Bontis (2001) and Sveiby (1997b) suggest that non-financial measurements can be developed using new proxies for intangible assets. These proxies should be based on employee competence, supplier relationships, brands, customers, and internal structures such as management and R&D. Sveiby (1997b) named this model the **Intangible Asset Monitor (IAM).** Sveiby identifies three key indicators for IAM: renewal, efficiency, and stability. He argues that intangible assets can create greater shareholder value than traditional measures if management focuses on them. IAM is applicable to various industries, not just manufacturing, and is especially relevant to the service sector, which drives knowledge organisations.

The **IC-Index** consolidates various indices into a single indicator. It is a company-specific measure that focuses on IC fluidity and considers past performance. The index is self-correcting and must reflect changes in a company's market capitalisation. Understanding the drivers and connections of the different measurements underpinning the IC-Index is essential for maximising its output (Bontis, 2001). The IC-Index has limitations as it is company-specific and cannot be widely applied. It is flawed when comparing different companies and its backward-looking approach may not accurately reflect future performance.

Economic Value Added (EVA™), developed by Stern Stewart, is a metric that reflects shareholder value creation or destruction (Iazzolino et al., 2013; Bodie et al., 2013; Correia et al., 2015). It comprises of net operating profit after tax (NOPAT), weighted average cost of capital (WACC), and invested capital/capital employed (k). EVA™ is an all-encompassing measure that determines value creation or destruction for shareholders and serves as a proxy for intellectual capital. EVA™, like other models, has shortcomings. It relies on historic book values, focuses only on physical capital (Pulic, 2004), and may not be a superior predictor of

share prices. Additionally, it assumes shareholder maximisation as the only fundamental objective, ignoring other interested parties (Bontis, 2001).

Stewart (1997) proposed using the **Market-to-Book ratio (MB)** to measure intellectual capital by comparing a company's market value to its book value. This measure is based on human and customer capital and is easy to understand. The difference between market value and book value is attributed to intellectual capital, which is supported by human and customer capital (Stewart, 1997). The measure has limitations. External factors like bond rates or inflation can impact share values or companies may adjust depreciation for tax benefits, affecting profitability and book value. Stock prices are often quoted below market values, especially during takeovers (Stewart, 1997).

Pulic (2004) as well as Firer and Mitchell Williams (2003) argue that comparing the measuring models is impossible due to their non-monetary basis, except for EVA™. Ante Pulic developed the **Value Added Intellectual Capital Model (VAIC™)** in 1998 to measure intellectual capital and potential (Pulic, 1998). VAIC™ is widely accepted for its simplicity in calculating IC within the research community (Firer and Mitchell Williams, 2003; Clarke et al., 2011).

Ståhle et al. (2011) suggests that Pulic's model uses company balance sheet figures to demonstrate the link between intellectual capital (IC) and economic performance. Intellectual capital must be utilised to extract value from the current business performance (Pulic, 2000). The VAIC™ index comprises three efficiency measures: capital employed efficiency (CEE), human capital efficiency (HCE), and structural capital efficiency (SCE).

Iazzolino and Laise (2013), Ståhle et al. (2011), and Marzo (2022) criticised VAIC™ despite its popularity among academics and researchers. For instance, they argued that Pulic's model has shortcomings in handling negative values, comparing non-capital-intensive industries, and defining intellectual capital. Andriessen (2004) also critiqued Pulic's model, highlighting issues related to the understanding of terminology and value creation process.

The original VAIC™ model by Pulic has been adapted and modified by scholars such as Nimtrakoon (2015), Xu and Liu (2020), Sowaity (2022), Nadeem et al. (2019), as well as Xu and Li (2022). These scholars have adjusted VAIC™ by adding components like relational capital (RC), innovation capital and treating them as investments in the value added calculation.

Despite its shortcomings, VAIC™ is popular among scholars due to its simplicity and the use of financial metrics in the calculation. It remains the most popular model used in prior research.

2.5 Empirical Research on IC, Performance and Firm Valuation

Bamel et al. (2022) discovered that IC research has significantly increased over the past two decades. Their study focused on scholarly articles published in the Journal of Intellectual Capital and confirmed that IC research predominantly covered developed countries. The research revealed that Italy, Australia, and the USA were the most extensively researched countries. In this review, we focus on research that specifically references VAIC™ and its extensions or modifications as measures of IC and review their relationship to firm performance and valuation. The following sections will cover individual-country and cross-country analyses across various sectors and periods, including developed and emerging markets.

2.5.1 Developed Market: Individual-Country Analysis

Meles et al. (2016) conducted empirical research using panel data from 5749 banks in the USA to determine whether the efficient use of IC positively impacted the banks' financial performance. The study covered the period from 2005 to 2012, and the data was extracted from Bankscope Bureau van Dijk, which contains specific balance sheet information used as control variables, including loan loss provision on total loans. The independent variables (HCE, SCE, and VAIC™) were regressed against the dependent variables return on average assets (ROAA) and return on average equity (ROAE) using multivariate regression analysis. The study also included control variables such as size, loan loss provision on total loans, total loans divided by total assets, gross domestic product (GDP), and the location of the bank's headquarters within the USA.

The study results showed that the relationship between HCE, VAIC™ and the dependent variables were positive and statistically significant. On the other hand, SCE's relationship with dependent variables reflected no statistical significance. The study did not specifically evaluate the CEE component. Nevertheless, the metric is part of the VAIC™ calculation. HCE and VAIC™ were positive and statistically significant in relation to ROAA and ROAE. The results demonstrated that the efficient use of human capital and VAIC™ have a positive impact on the financial performance of banks in the USA. Notwithstanding, Meles et al. (2016) cautioned against generalization of the results due to potential bias, regardless of the sample size. The authors assert that the result might be more generalizable if the sample is expanded to include other countries.

Nadeem et al. (2018) also studied the relationship between IC, its components, and firm performance utilising the GMM econometrics model. The authors posit that previous studies used OLS or fixed-effects estimators, producing contradictory results. Nadeem et al. (2018) sampled 571 listed firms on the Australian Stock Exchange between 2005 and 2014 across various economic sectors. Time series data was extracted from Bloomberg. The study

included the control variables asset turnover and price-to-book ratio. The results of the study found that IC has a positive relationship with firm performance represented by return on equity (ROE) and return on assets (ROA). The model outcome was positive and statistically significant at a 1% level.

The results of Nadeem et al. (2018) support the assertion of Meles et al. (2016) that increased investment in IC support improved financial performance. The fundamental difference between these two studies relates to the econometrics models used. The OLS regression model is unidirectional, whereas Nadeem et al. (2018) posit the GMM model is bidirectional. In other words, as much as IC has an impact on firm performance, firm performance can also have an impact on IC. Moreover, increased firm performance could lead to greater resources allocated to IC investment and value creation (Nadeem et al., 2018). Nadeem et al. (2018) recommended expanding the research to include other regions akin to Meles et al. (2016).

Joshi et al. (2013) examined the relationship between IC and firm performance in the Australian financial sector from 2006 – 2008. Joshi et al. (2013) collected secondary accounting data from Finanalysis & Connect 4. The authors regressed the data by using OLS multiple regression and analysis of variance (ANOVA) methods. Fundamentally, Joshi et al. (2013) only made use of a single dependent variable (ROA) compared to Meles et al. (2016) and Nadeem et al. (2018), who made use of two or more dependent variables. The dependent variable was regressed against the VAIC™ components. Control variables included company size and financial sub-sectors. The study found that ROA had no statistically significant relationship with HCE and SCE. Notwithstanding, ROA displayed a positive and statistically significant relationship with CEE. The results suggest that IC does not significantly impact the profitability of financial sector firms within Australia. However, physical or tangible capital is, in fact, a better predictor of positive firm performance in the future. Joshi et al. (2013), acknowledged that the single-sector view was a limitation of their work, and that further research should include a broader sector-based approach.

Zeghal and Maaloul (2010) investigated the impact of VAIC™ in relation to the firm's economic and financial performance as well as its market value. The study included 300 listed UK companies within the high-tech, traditional, and service sectors. The study focused on a single period (2005). Data was extracted from the "value-added scoreboard" obtained from the UK Department of Trade and Industry. The dependent variables, economic, financial performance, and market value are represented by operating income to sales (OI/S), ROA, and market value to book value (MB), respectively. The authors used size and leverage as control variables.

Using OLS multiple regression and ANOVA statistical models, Zeghal and Maaloul (2010) demonstrated a positive and statistically significant relationship between intellectual capital efficiency (ICE), represented by HCE and SCE, and the dependent variables. The results indicate that IC positively contributes to the economic and financial performance as well as the market value of the companies. However, CEE showed mixed results in its relationship with the dependent variables. It was statistically significant and negatively related to economic performance, suggesting the presence of additional expenses or non-homogeneous metrics. On the other hand, CEE was positively related and statistically significant in its relationship with financial performance and market value, due to product cost decreases. Although CEE's relationship was statistically significant across various sectors, it was not significant at an individual sector level in explaining the relationship with firm economic performance (Zeghal and Maaloul, 2010). Additionally, CEE showed no statistical significance in the high-tech sector in relation to the relationship between ROA and CEE but was significant in its relationship with MB in the high-tech industry, indicating that value-added activities lead to increased market valuation in this sector. The study has limitations, including the use of a cross-sectional approach instead of a time-series method. Zeghal and Maaloul (2010) suggest that additional control variables could yield different results.

Similar to Joshi et al. (2013) and Nadeem et al. (2018), Clarke et al. (2011) conducted empirical research on the relationship between VAIC™ and firm performance of listed Australian firms across all sectors of the economy. The study included a sample of 1676 firms from 2004 to 2008 and utilised secondary data from Compustat Global Vantage. The data was analysed using OLS Multiple regression and included control variables such as leverage, R&D intensity, year, and industry. The response variables were ROA, ROE, revenue growth (RG), and employee productivity (EP). The results of the study demonstrated that VAIC™, HCE, and CEE are statistically significant and positively related to all the variables studied. The authors acknowledged potential statistical challenges with the models used and recommended employing a more refined model, as well as considering performance lags of more than one year.

Sardo et al. (2018) focussed their research on small and medium-sized (SME) enterprises within Portugal’s hotel industry. The authors investigated the relationship between IC and the financial performance of 934 hotels between 2007 and 2015. Secondary data was collected from Amadeus and Moody’s Analytics, and the study adopted the GMM econometric model to investigate the unbalanced panel data. Control variables included size, age, and leverage. The IC components (HCE and SCE) including RCE was regressed against ROA and found to be statistically significant and positive relative to ROA. The authors suggested that we need to consider different proxies to understand if the results will vary. For example, they proposed

including "training and development expenses and marketing or advertising expenses" (Sardo et al., 2018:73) as variables. Another limitation of the study is that it did not test the delayed relationship between IC components.

In the context of the developed world, the narrative of these studies for individual countries illustrates mixed and inconclusive results. For example, Joshi et al. (2013) demonstrates no statistical significance in the relationship between the components of IC and ROA, whereas Nadeem et al. (2018) and Sardo et al. (2018) found evidence that the relationship was positive and statistically significant between the said dependent and independent variables. Similarly, these studies made use of divergent econometric models, notwithstanding their limitations. For example, Nadeem et al. (2018) and Sardo et al. (2018) made us of GMM estimator technique to analyse the data whereas the rest of the studies made use of OLS regression models and ANOVA which in part could explain the reasons for the contrasting results. The extent of the sample size varied significantly from 33 (Joshi et al., 2013) to 5749 (Meles et al., 2016). Noticeably only Zeghal and Maaloul (2010) tested for the relationship between IC and firm valuation, whilst Nadeem et al., (2018) included the metric as a control variable. Sector focus was mixed although some authors focused on sector specific analysis (Joshi et al., 2013; Sardo et al., 2018). It is noteworthy to mention that size and leverage were the dominant control variables across the studies. The dependent variable proxies were mixed across the studies with some using multiple dependent variables (Clarke et al., 2011; Zeghal and Maaloul, 2010) to measure firm performance whilst others only used a single metric (Joshi et al., 2013; Sardo et al., 2018).

Although the developed markets made strides to understand the relationship between VAIC™, its components and firm performance, the extent to which these variables impact the emerging markets from an individual country perspective requires consideration. This is the focus of the next section of this review.

2.5.2 Emerging Market: Individual-Country Analysis

Considering the research aim and objectives as outlined in section 1.3, greater emphasis is placed on analysing the literature from an emerging market perspective. The studies under review investigate VAIC™, modified or extended VAIC™, its components (HCE, SCE, RCE, CEE), and its relationship with various dependent variables. Most studies used control variables apart from one (Chen et al., 2005). An array of control variables is used. However, size and leverage are the common constants. The studies cover the following countries, namely South Africa, Jordan, India, Taiwan, Mauritius, Indonesia, Vietnam, South Korea, Thailand, China, Ghana, and Brazil.

The sample sizes used by the researchers varied from sixteen (Tran and Vo, 2018) to 4254 (Chen et al., 2005). Seven out of fifteen studies conducted their investigations on mixed economic sectors (Firer and Mitchell Williams, 2003; Firer and Stainbank, 2003; Bhattu-Babajee and Seetanah, 2022; Smriti and Das, 2018; Chen et al., 2005; Soetanto and Liem, 2019; Morris, 2015;) while eight studies focused on two or less sectors (Xu and Li , 2022; Xu and Liu , 2020; Britto et al., 2014; Oppong et al., 2019; Tran and Vo, 2018; Le et al., 2022; Maji and Goswami, 2016; Sowaity, 2022). The researchers made use of a variety of econometric models. Across the various studies, the OLS linear multiple regression analysis was mainly used (Britto et al., 2014; Xu and Li, 2022; Xu and Liu, 2020; Morris, 2015; Chen et al., 2005; Maji and Goswami, 2016; Sowaity, 2022; Firer and Mitchell Williams, 2003; Firer and Stainbank, 2003). Data was sourced from third-party service providers, e.g., Bloomberg, McGregor BFA, or hand-collected annual financial statements from publicly listed companies. Firer and Mitchell Williams (2003) as well as Firer and Stainbank (2003) are the only authors who used a single-year period in their investigations compared to the other authors who used longitudinal data.

HCE's impact on firm performance and firm value has been inconclusive in emerging markets. For example, Firer and Mitchell Williams (2003) found a statistically significant and negative relationship between HCE and firm valuation, whereas Chen et al. (2005), Morris (2015), and Bhattu-Babajee and Seetanah (2022) found a positive and statistically significant relationship between HCE and firm valuation. On the other hand, some researchers found no statistical significance between HCE and firm value (Smriti and Das, 2018; Xu and Liu, 2020). Similarly, researchers found no statistical significance between HCE and firm performance (Firer and Mitchell Williams, 2003) and in other instances positive and statistically significant association was established between the said dependent and independent variable (Soetanto and Liem, 2019; Bhattu-Babajee and Seetanah, 2022). The reasons for the inconclusive or contrasting results can be attributable to the trade-off management has to make between physical capital and human capital (Firer and Mitchell Williams, 2003) or the fact that investors do not realise the importance of HCE as a contributor towards value creation and thus do not invest to unlock the innovation capabilities, skills and competencies of their staff (Smriti and Das, 2018).

The relationship between SCE, firm performance, and valuation was inconclusive (Xu and Liu, 2020; Chen et al., 2005). Firer and Mitchell Williams (2003) suggest that the relationship between SCE and productivity (ATO) and SCE and firm valuation (MB) has no explanatory power. However, the relationship between SCE and firm performance is positive and statistically significant. The Smriti and Das (2018) results again contradicted Firer and Mitchell Williams (2003). They found that SCE positively affects productivity and firm valuation, but that SCE has no relationship with firm performance. Smriti and Das (2018) argue this result is

evidence that the sample firms are more efficient in optimally deploying their internal resources, which includes improving their employees' knowledge base, which in turn can be used to generate innovative ideas, process enhancements and development of patents.

The VAIC™ model was modified to include RCE in the hope of addressing its original shortcomings (Xu and Li, 2022). Some authors, such as Xu and Li (2022), Sowaity (2022), Xu and Liu (2020), including Soetanto and Liem (2019), have presented conflicting results regarding the relationship between RCE and firm performance. Xu and Liu (2020) found a statistically negative relationship between RCE and firm performance, whereas Xu and Li (2022) demonstrated a statistically positive relationship. Additionally, Xu and Liu (2020) found no statistical relationship between RCE and productivity, while Xu and Li (2022) showed a positive relationship. According to Xu and Li (2022), these results suggest that management should focus on improving relationships with suppliers and customers to enhance value added.

In studies on emerging market economies, the relationship between capital employed efficiency (CEE) and firm valuation varies. Some studies, such as Firer and Mitchell Williams (2003), Chen et al. (2005), as well as Smriti and Das (2018), found a positive and statistically significant relationship. However, other studies, like Soetanto and Liem (2019) including Xu and Liu (2020), found no statistically significant relationship and no explanatory power. There were also studies that tested the relationship between CEE, firm performance, and productivity. Apart from Firer and Mitchell Williams (2003) and Bhattu-Babajee and Seetanah (2022), which found no relationship between CEE and productivity or CEE and performance, most authors found a positive relationship when testing these variables (Maji and Goswami, 2016; Chen et al., 2005; Soetanto and Liem, 2019; Xu and Liu, 2020; Tran and Vo, 2018; Xu and Li, 2022; Britto et al., 2014). One study by Smriti and Das (2018) reflected a negative relationship between CEE and productivity. While the results are mixed and inconclusive, it can be inferred that CEE is the main driver of firm performance (Smriti and Das, 2018).

VAIC™, its adjusted, modified or extended version is generally tested in conjunction with the individual components that makes up the index. However, Firer and Stainbank (2003) only tested for VAIC™ and its relationship with firm performance, firm productivity and firm valuation. The results were mixed. For example, the authors found a positive relationship with ROA, a negative relationship with ATO, and statistically no relationship with market-to-book ratio. Chen et al. (2005), Smriti and Das (2018), Bhattu-Babajee and Seetanah (2022) and Le et al. (2022) on the other hand found a positive relationship between VAIC™ and all the dependent variables. Soetanto and Liem (2019) found positive relationship between mVAIC™ and ROA but no statistical significance with firm value. This result contradicts in part the results

of Xu and Li (2022) who found statistically significant and positive relationship between mVAIC™ and firm performance as well as mVAIC™ and firm productivity.

In summary, the results of the emerging market studies, similar to those of developed markets, are inconclusive and mixed regarding IC and its components in relation to firm performance and firm valuation.

2.5.3 Cross-Country Analysis

We reviewed five cross-country studies. Three of the studies were based on emerging markets (Olarewaju and Msomi, 2021; Nimtrakoon, 2015; Nadeem et al., 2017), while Nadeem et al. (2019) based their study on developed, developing and frontier markets. Sardo and Serrasqueiro (2018) studied the developed market in Europe.

Two studies utilised two or more econometric techniques which included static and dynamic regressions to test the relationship between the various dependent and independent variables. Four studies made use of the GMM dynamic panel regressions techniques compared to Nimtrakoon (2015) that only made use of static regression models.

For example, Sardo and Serrasqueiro (2018) empirically researched the relationship between IC, growth opportunities, financial performance, including IC's impact on across fourteen Western European countries. The authors used the generalised method of moments (GMM) system econometrics model to estimate and regress the data. Sardo and Serrasqueiro (2018) focused on mixed sectors classified into high-tech, medium-tech, and low-tech firms. The study only regressed VAIC™ against the dependent variables ROA and Tobin's Q and made use of control variables, namely cash flow, leverage, size, and crises. Similarly, Nadeem et al. (2019), only focused on a single independent variable, mVAIC, but regressed it against two firm performance dependent variables, ROA and ROE. Nadeem et al. (2019), Sardo and Serrasqueiro (2018) and Nadeem et al. (2017), did not discriminate based on sectors compared to Olarewaju and Msomi (2021) and Nimtrakoon (2015) who focused on a particular sector which they deemed to be highly correlated with knowledge workers.

The studies in general reflect that VAIC™ has a positive and statistically significant relationship with ROA and ROE (firm performance). Sardo and Serrasqueiro (2018) claim that the relationship demonstrates that efficient utilisation of HCE, SCE, and CEE improves firm performance and is aligned with previous empirical research. Nadeem et al. (2019) displayed comparable results to Sardo and Serrasqueiro (2018), notwithstanding that they tested modified VAIC™.

Results associated with the individual components of VAIC™ were mixed. The three studies (Nadeem et al., 2017; Olarewaju and Msomi, 2021; Nimtrakoon, 2015) found a positive

association between HCE and firm performance. The authors postulate that the results support the assertion that increases in human capital drives increased firm capabilities and performance. SCE had a positive association with firm performance in general, however Nadeem et al. (2017) noted that South Africa had negative relationship between ATO and SCE. Nimtrakoon (2015) found no statistical significance between firm performance and SCE. The study of Olarewaju and Msomi (2021) found no significance between CEE and firm performance suggesting that firms in SADC's insurance industry was inefficient in deploying their financial resources to enhance firm performance.

Nadeem et al. (2017) and Nimtrakoon (2015) also tested the relationship between firm valuation and the components of VAIC™ and the index and found that there is a positive and significant relationship. Sardo and Serrasqueiro (2018) only tested the relationship between VAIC™ and firm valuation and found similar results to the former authors. However, Sardo and Serrasqueiro (2018) did find that in low technology (low-tech) driven sectors, there is a negative relationship between VAIC™ and Tobin's Q which suggest that low tech firms are less efficient in utilising their resources. It might also suggest that there is less need to reinvest in IC enhancing activities given the sector dynamics such as lower requirements of innovation and to upgrade technology skills.

2.5.4 Impact of time-lags on firm performance

Some quantitative empirical research on IC utilised linear multiple regression analysis and regressed the data for the current period only (Firer and Stainbank, 2003; Firer and Mitchell Williams, 2003; Morris, 2015; Britto et al., 2014; Maji and Goswami, 2016; Xu and Liu, 2020). Firer and Stainbank (2003) opined that whilst the theoretical aspect of their regression analysis is correct, the study suffered from not lagging the variables. However, notwithstanding making use of less sophisticated models, other studies did include lagged models (Chen et al., 2005; Clarke et al., 2011; Meles et al., 2016). For example, Clarke et al. (2011) demonstrated that the previous year's VAIC™, HCE and SCE is statistically significant and positive with firm performance except revenue growth. This result is similar to the finding of Chen et al. (2005).

Nadeem et al. (2018), posit that history has an influence on the future, hence the variables must be lagged. However, it is unclear how many lags are appropriate given too few or too many lags may influence the specification test of the model employed (Nadeem et al., 2018). Moreover, the authors suggest that the generalised method of moments (GMM) is the preferred instrument to take history into account and deals with the endogeneity problem. Subsequently, studies make use of system GMM as sole model or in combination other models for their investigations (Sardo and Serrasqueiro, 2018; Sardo et al., 2018; Oppong et al., 2019; Nadeem et al., 2018; Olarewaju and Msomi, 2021).

For example, Nadeem et al. (2018) demonstrated that the dynamic GMM models was statistically significant and positive for VAIC™, IC components and CEE in relation to firm performance and statistically performed better compared to the static models.

2.6 Summary and Conclusion

In this chapter, we defined IC and its components and provided an overview of the prominent non-monetary and monetary IC models. We also discussed the models' benefits and drawbacks. We unpacked the various literature around IC and its relationship with firm performance and valuation and found that across the developed and emerging markets, the results remain inconclusive. Notwithstanding, the discussion demonstrates that there is limited research regarding IC's relationship with firm performance and firm valuation on a cross-country basis and that most research centres around individual-country investigations.

The next chapter will outline the research methodology, coupled with the data collection and sampling methods. We will also discuss the statistical methods that will be applied, followed by a discussion of the results and conclusion.

CHAPTER 3: RESEARCH METHODOLOGY AND PROCESS

3.1 Introduction

This chapter will outline the research approach, describe the research methodology and process that will be applied. The section will also address the limitations of the sample and describe the variables that will be used in calculating the results. Finally, the chapter will conclude by examining the factors that limit the study and providing a summary.

3.2 Research Problem

As outlined in Chapter 1, South Africa is the most industrialised country on the African continent (Morris, 2015; Quaynor et al., 2022). However, the country is marred by weak economic performance in the wake of low GDP growth, elevated levels of unemployment, and unskilled labour (UNDP, 2022). Human capital is a fundamental catalyst for firm performance, technological advancement, and innovation (Morris, 2015). Consequently, it is important for South African companies to understand how IC, represented by human capital and structural capital can function as means towards value creation and firm performance.

The research on IC and its influence on firm performance has focused on analysing single countries. With some exception (e.g. Nimtrakoon, 2015; Nadeem, 2016), these studies have been limited by small sample sizes and constrained data availability. Additionally, the studies in certain instances only focused on IC-intensive or single sectors of the economy, thus precluding other sectors where IC can also be impactful (Firer and Mitchell Williams, 2003). Consequently, the generalisation of these findings is challenging. Whilst the impact of IC on firm performance and market value has been widely researched for countries on a standalone basis, studies of cross-country emerging market economies have been limited (Nimtrakoon, 2015; Nadeem et al., 2017; Maluleke, 2020; Olarewaju and Msomi, 2021). The problem is that we know very little about the impact of investment in intellectual capital across emerging markets to which the South African experience could be measured. This is a gap in the literature that this study aims to address. Its focus is on understanding how the relationship between IC and the firm performance of South African companies compared to that of other emerging market economies.

3.3 Research Objectives

The study aims to examine the relationship between intellectual capital, firm performance, and firm value by making use of VAIC™ as per Pulic (2000) and accounting metrics (Chen et al., 2005; Nimtrakoon, 2015; Nadeem et al., 2017; Sardo and Serrasqueiro, 2018; Olarewaju and Msomi, 2021) by taking a look at emerging market countries, namely South Africa, Indonesia and Brazil.

The research objectives of the study are as follows:

- To determine the relationship between VAIC™ and firm performance
- To determine the relationship between VAIC™ and firm market value
- To determine the relationship between the components of IC and firm performance
- To determine the relationship between the components of IC and firm market value
- In each of the instances above, to provide a comparison of the outcome for South African firms with that of the other countries included in the study.

3.4 Research Questions

The following research questions are derived informed by the aforementioned objectives:

- What is the relationship between VAIC™ and the firm's performance in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between VAIC™ and the firm's market value in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between the components of IC and the firm's performance in emerging market countries of South Africa, Indonesia, and Brazil?
- What is the relationship between the components of IC and the firm's market value in emerging market countries of South Africa, Indonesia, and Brazil?

3.5 Hypotheses

The hypotheses are formulated to achieve the objectives and answer the research question of the study, hypotheses are be formulated to test VAIC™, its components and the relationship with firm performance and firm market value based on prior studies (Chen et al., 2005; Nimtrakoon, 2015; Nadeem et al., 2017; Sardo and Serrasqueiro, 2018; Olarewaju and Msomi, 2021).

- $H_{1(a)}$ = HCE has a positive relationship with the return-on-assets ratio.
- $H_{1(b)}$ = HCE has a positive relationship with the asset-turnover ratio.
- $H_{1(c)}$ = HCE has a positive relationship with market value-to-book value ratio.

- $H_{2(a)}$ = SCE has a positive relationship with the return-on-assets ratio.
- $H_{2(b)}$ = SCE has a positive relationship with the asset-turnover ratio.
- $H_{2(c)}$ = SCE has a positive relationship with the market value-to-book value ratio.

- $H_{3(a)}$ = CEE has a positive relationship with the return-on-assets ratio.
- $H_{3(b)}$ = CEE has a positive relationship with the asset-turnover ratio.
- $H_{3(c)}$ = CEE has a positive relationship with the market value-to-book value ratio.

- $H_{4(a)}$ = VAIC™ has a positive relationship with the return-on-assets ratio.
- $H_{4(b)}$ = VAIC™ has a positive relationship with the asset-turnover ratio.
- $H_{4(c)}$ = VAIC™ has a positive relationship with the market value-to-book value ratio.

3.6 Paradigm

This study is based on a deductive approach, which follows a positivist rather than an interpretivist paradigm. Rehman and Alharthi (2016) posit that positivism is reality that exists separate from human perceptions. Positivism as an epistemological position emphasises objectivity in understanding and interpreting knowledge. This paradigm lends itself to internal validity. Rehman and Alharthi (2016) states that where the results are generalisable, the research has external validity compared to the interpretivist approach that opposes the positivist views (Bryman et al., 2017). The interpretivist approach attempts to explain and understand human behaviour, whereas positivists critically engage with the relationship between theory and research (Bryman et al., 2017).

This research adopts a quantitative approach which follows the methodologies of prior research (Chen et al., 2005; Nimtrakoon, 2015; Nadeem et al., 2017; Sardo and Serrasqueiro, 2018; Olarewaju and Msomi, 2021).

3.7 Research Methodology

We employed quantitative research utilising longitudinal data, using the two-step difference generalised method of moments (DGMM) to model the data and observe the relationship between firm performance and firm valuation (Nadeem, 2019; Sardo and Serrasqueiro, 2018; Olarewaju and Msomi, 2021). Additionally, we use the static and dynamic OLS models to check the robustness of the GMM model (Nadeem et al., 2017).

De Jager (2008) posits that longitudinal or panel data is frequently used in accounting research as it allows for investigation across time and firms. Additionally, pooling the data allows the researcher to increase the degrees of freedom when the time span is short and, in turn, reduce the standard error of the coefficients. Moreover, panel data can account for the complexities in relationships through the utilisation of sophisticated models between variables compared to cross-section or time-series data (Hsiao, 2007; Baltagi, 2005).

Apart from the aforementioned, Baltagi (2005) postulates that panel data has the following benefits:

- Panel data controls for individual heterogeneity, whereas time-series or cross-section studies may not control for this, leading to biased regression results.
- Panel data allows for dynamic changes in variables.
- Panel data can recognise, and measure influences that pure cross-section and time series data is unable to.

3.7.2 Statistical Models

Sixty-five percent (17 out of 26) of the journal articles reviewed make use of OLS and or FE regression models to study the relationship of VAIC™, firm performance and firm valuation, for example, Firer and Mitchell Williams (2003), Clarke et al. (2011), Chen et al. (2005) and Maji and Goswami (2016). Notwithstanding the popularity of these models, it suffers from certain drawbacks, for example, failing to control for unobserved heterogeneity across firms or time in the case of OLS and cannot estimate the impact of time-invariant variables given its absorption into the FE model (Maji and Goswami, 2016; Baltagi, 2005; Nadeem et al., 2017).

Nadeem et al. (2019) adopted the difference GMM approach by investigating the relationship between VAIC™ and firm performance across developed, emerging and frontier markets. The model can "fit linear models with one dynamic dependent variable, additional controls and fixed effects" (Roodman, 2009a:137). GMM enables the lagging of the dependent variable and, therefore, accounting for the endogeneity problem of the regressor (Wintoki et al., 2012; Nadeem et al., 2017). In other words, IC impacts firm performance; however, the past performance of the firm can also impact IC. To avoid dynamic panel bias, the model requires careful specification, including testing for instrument validity (Sargan test) and the absence of serial correlation (second-order autoregression) (Roodman, 2009b; Windmeijer, 2005; Nadeem, 2016). While the difference GMM controls for unobserved heterogeneity by differencing out the individual effects, the method can suffer from weak instruments if the lagged variable is not strongly correlated with the differenced variables (Arellano and Bond, 1991; Blundell and Bond; 1998).

Given the aim of this study insofar as analysing VAIC™, its components, firm performance and firm valuation on a cross-country basis, we adopted a similar econometric approach as Nadeem et al. (2019) and Nadeem et al. (2017) given the stated benefits and also test for robustness of the DGMM making use of static and dynamic OLS.

Nadeem et al. (2017) suggest that the dynamic nature of a dependent variable can be tested with a static and dynamic OLS. If the lagged or dynamic OLS R^2 increases three to four times

and is statistically significant compared to the R^2 static OLS, the change is reflective of a dynamic relationship between the dependent variable and lagged dependent variable.

We used **R studio** to run the various models. The static and lagged OLS models are represented by the following equations:

Static OLS:

$$FP_{it} = \alpha + \beta X_{it} + \beta Z_{it} + \eta_i + \varepsilon_{it} \quad (1)$$

Dynamic OLS

$$FP_{it} = \alpha + FP_{it-1} + \beta X_{it} + \beta Z_{it} + \varepsilon_{it} \quad (2)$$

Where:

FP_{it} = firm performance for a firm i at time t

$FP_{i,t-1}$ = lagged firm performance

α = the intercept term

X_{it} = the independent variable for a firm i at time t

Z_{it} = the control variables for a firm i at time t

η_i = unobserved firm specific effect for firm i

ε_{it} = error term for a firm i at time t

The DGMM model, including lagged firm performance variable, is presented by the following equation:

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 X_{1\,it} + \beta_3 X_{2\,it} + T.\lambda + \eta_i + \varepsilon_{it} \quad (3)$$

Where:

FP_{it} = firm performance for a firm i at time t

$LFP_{i,t-1}$ = lagged firm performance

α = the intercept term

$X_{1\,it}$ = the independent variable for a firm i at time t

$X_{2\,it}$ = the control variable for a firm i at time t

T.λ = vector of time dummies

η_i = unobserved firm specific effect for firm i

ε_{it} = error term for a firm i at time t

3.7.3 Independent Variables: Intellectual Capital

VAIC™ was utilised as a measurement instrument to test IC efficiency (Pulic, 2000). VAIC™ is the sum of HCE, SCE and CEE. These four variables - HCE, SCE, CEE and VAIC™ - represent the explanatory variables in our model and are popular in the IC discourse given the simplicity that underlies the calculation (Nimtrakoon, 2015; Maji and Goswami, 2016; Nadeem et al., 2019; Marzo, 2022). Value Added (VA) is a key component of the VAIC™ calculation. VA is defined as the difference between revenue (output) and expenses (input). Revenue is regarded as all the turnover generated from selling products and services. Expenses encompass the associated costs incurred to operate the business, excluding employee costs (Pulic, 2000). Pulic (2000) regards employee costs as an investment critical in the value-creation process.

The equation for VA is expressed as follows:

$$VA_i = EBIT_i + D_i + A_i + EC_i \quad (4)$$

Where:

VA_i = Value added of firm i.

$EBIT_i$ = Earnings before interest and tax of firm i.

D_i = Depreciation of firm i.

A_i = Amortization of firm i.

EC_i = Employee cost of firm i which includes total salaries and wages

The efficiency ratios of HCE, SCE, CEE and VAIC™ is derived with the following expressions:

$$HCE_i = \frac{VA_i}{HC_i} \quad (5)$$

$$SCE_i = \frac{SC_i}{VA_i} \quad (6)$$

$$CEE_i = \frac{VA_i}{CE_i} \quad (7)$$

$$VAIC™_i = HCE_i + SCE_i + CEE_i \quad (8)$$

Where:

VA_i = Value added of firm i.

HCE_i = Human capital efficiency of firm i.

HC_i = Human capital for firm i encompassing the total salaries and wages.

SCE_i = Structural capital efficiency of firm i.

SC_i = Structural capital for firm i computed as the difference between VA_i and HC_i.

CEE_i = Capital employed efficiency for firm i.

CE_i = Capital employed for firm i computed as the net asset value of the business, presented as the difference between total assets and total liabilities.

Nimtrakoon (2015), Soetanto and Liem (2019) as well as Nadeem et al. (2019) augmented VAIC™ to an extended or modified VAIC™ model. They argue that the original VAIC™ model was insufficient as it did not account for relational capital, omitted R&D costs as an investment in the value creation process and contains "perfect superimposition" given that SCE = 1 - $\frac{1}{HCE}$ or HCE = $\frac{1}{1-SCE}$ as postulated by Ståhle et al. (2011:536). This study makes use of the original VAIC™ model which has broad support in research notwithstanding its criticism (Marzo, 2022). Additionally, a delimitation of the study was the lack of disclosure by the countries in respect of R&D and to extend the VAIC™ model in order to deal with the critique of Ståhle et al. (2011).

3.7.4 Dependent Variables

The dependent variables used in the study were return-on-assets (ROA), asset-turnover (ATO) and market-to-book value (MB). ROA and ATO are proxies for firm performance while MB represents firm valuation.

Across the various studies, these variables are used as proxies to establish the relationship with the explanatory variables (Firer and Stainbank, 2003; Firer and Mitchell Williams, 2003; Xu and Liu, 2020; Smriti and Das, 2018).

$$\text{ATO} = \frac{Revenue1}{Total\ assets} \quad (9)$$

$$\text{ROA} = \frac{Net\ profit}{Total\ Assets} \quad (10)$$

$$\text{MB} = \frac{Market\ Capitalization}{Net\ Asset\ Value\ (Equity)} \quad (11)$$

3.7.5 Control Variables

The control variables in the study namely size and leverage, followed the research of Britto et al. (2014), Zeghal and Maaloul (2010) as well as Nadeem et al. (2017) where these are defined as follows:

Size = Natural logarithm of market capitalisation of firm i. (12)

Leverage $= \frac{Total\ Liabilities}{Net\ Asset\ Value\ (Equity)}$ of firm i. (13)

In table 1 we show the various descriptors used in the R studio modelling that represents the variables in equations 5 – 13.

Table 1. R Studio Descriptors

Dependent Variable	**Equation No.**	**R Studio Descriptor**
Return-on-Assets Ratio	10	ROA1
Asset Turnover Ratio	9	ATO1
Market-to-Book Value	11	MB1
Independent Variable		**R Studio Descriptor**
Human Capital Efficiency	5	HCE1
Structural Capital Efficiency	6	SCE1
Capital Employed Efficiency	7	CEE1
Value Added Intellectual Capital	8	VAIC1
Control Variables		**R Studio Descriptor**
Leverage Ratio	13	Lev_ratio1
Size	12	Size1

3.8 Research Process

3.8.1 Data Collection

The initial data set was obtained from Eikon Refinitiv Datastream. The data set is sector, market capitalisation agnostic and consists of 1504 companies listed on the stock exchanges of Brazil, South Africa, and Indonesia (Nadeem et al., 2017; Sardo and Serrasqueiro 2018). The data in table 2 initially spanned a ten-year period from 2014 to 2023 and was compared with Bloomberg to ensure data integrity. Shakil (2021) suggests that Eikon Refinitiv Datastream provides comprehensive historical and current financial information of listed firms. Moreover, the platform is regularly used by academia and the data is regarded as reliable (Shakil, 2021).

Salaries and wages is a key input of VAIC™. The data was trimmed by eliminating companies that did not report salaries and wages or had up-to-date financial information for at least the recent five consecutive years (Smriti and Das, 2018). This resulted in the data set being truncated to 787 companies across the three countries (see table 2). We consider the most

recent five-year period and the sample size appropriate to conduct the analysis supported by research from Clarke et al. (2011), Britto et al. (2014) including Xu and Li (2022). The distribution per sector in Indonesia is well-balanced, whereas Brazil and South Africa reflect a larger share towards consumer staples, consumer discretionary, industrials and utilities. Healthcare, information technology and energy sectors are the least represented in the sector distribution across the Brazil and South Africa in the final sample (see tables 3, 4 and 5).

Table 2. Country Distribution

Country	No of Companies Distribution Before	Excluded Companies Less	No of Companies Distribution After	Percentage After
Brazil	344	-136	208	26%
Indonesia	881	-458	423	54%
South Africa	279	-123	156	20%
Grand Total	**1504**	**-717**	**787**	**100%**

Table 3. The distribution per sector – Brazil

Sectors - Brazil	Before truncation	After truncation
Communication Services	15	5
Consumer Discretionary	76	43
Consumer Staples	31	16
Energy	10	4
Financials	40	29
Health Care	18	9
Industrials	56	32
Information Technology	10	3
Materials	27	19
Real Estate	19	11
Utilities	42	37
Grand Total	**344**	**208**

Table 4. The distribution per sector – Indonesia

Sectors - Indonesia	Before truncation	After truncation
Communication Services	49	30
Consumer Discretionary	123	49
Consumer Staples	116	54
Energy	57	35
Financials	108	77
Health Care	34	13
Industrials	156	60
Information Technology	38	12
Materials	99	46
Real Estate	92	43
Utilities	9	4
Grand Total	**881**	**423**

Table 5. The distribution per sector – South Africa

Sectors - South Africa	Before truncation	After truncation
Communication Services	12	8
Consumer Discretionary	33	24
Consumer Staples	26	19
Energy	7	2
Financials	50	22
Health Care	6	4
Industrials	36	18
Information Technology	16	6
Materials	48	29
Real Estate	43	24
Utilities	2	-
Grand Total	**279**	**156**

3.8.2 Outlier Detection

Adequate outlier identification is essential, especially in quantitative research. Ignoring it could result in spurious or incorrect inferences. Sullivan et al. (2021) posit that there are various techniques by which outliers can be identified and handled. Some of these methods include trimming, winsorising, standard deviation, Wilks' statistic, interquartile range, studentised residuals, to name a few. Sullivan et al. (2021) further suggest that adoption of a method is not a "one-size-fits-all" approach, and a combination of the various methods must be employed to conclude on the robustness of the results and develop a trend. Additionally, some of the

methods apply to univariate regressions, while others are more appropriate for multivariate regressions.

Sullivan et al. (2021) postulate that the interquartile range (IQR) method is robust to the masking effect. In other words, it does not hide the impact of other influential data points in the data. Additionally, Maluleke (2020) suggests that IQR is suited to non-normal distributions. It is expected that our data set will be non-normal given the use of financial ratios (Jofre-Campuzano and Coenders, 2022; Morris, 2015), therefore making IQR method suited to identify outliers compared to other outlier detection methods such as the multivariate method, e.g. Mahalanobis distance squared, that relies on a normal distribution.

We utilised the following formula to identify likely outliers (Hoaglin et al., 1986). Values outside of the lower bound and upper bound were treated as probable outliers.

Lower bound = $Q_1 - g * (Q_3 - Q_1)$ (14)

Upper bound = $Q_3 + g * (Q_3 - Q_1)$ (15)

Where:

Q_1 = first quartile (25%)

Q_3 = third quartile (75%)

g = multiplication factor of 1.5

After the outliers have been detected, the researcher must decide how to deal with them. Some techniques include trimming, winsorisation, robust estimation method or retention of the outliers in the data (Rousseeuw and Hubert, 2011; Ghosh and Vogt, 2012). Trimming requires the elimination of the outlier from the data set (Zeghal and Maaloul, 2010; Sardo et al., 2018; Sardo and Serrasqueiro, 2018), while winsorisation encompasses reducing the outlier to a value closer to a common value in the array (Morris, 2015). We opted to winsorise the data instead of eliminating the outliers to maintain data integrity. Table 6 depicts the impact of outlier detection on the sample.

Table 6. Outliers per dependent variable

Country	**Observations**	**Outliers Detected**		
		ROA	**ATO**	**MB**
Brazil	1040	115	14	119
Indonesia	2115	206	136	254
South Africa	780	70	61	46
	3935	**391**	**211**	**419**

The histograms in Figures 1 to 9 show how the winsorisation process affects the dependent variables of different countries. From these, we can observe the influence of the winsorisation process on the edge of the tails. We notice more values on the edge of the tails due to the transformation of the outliers to the nearest common value instead of trimming, as postulated by Ghosh and Vogt (2012).

Figure 1. Brazil_ROA: untransformed versus transformed

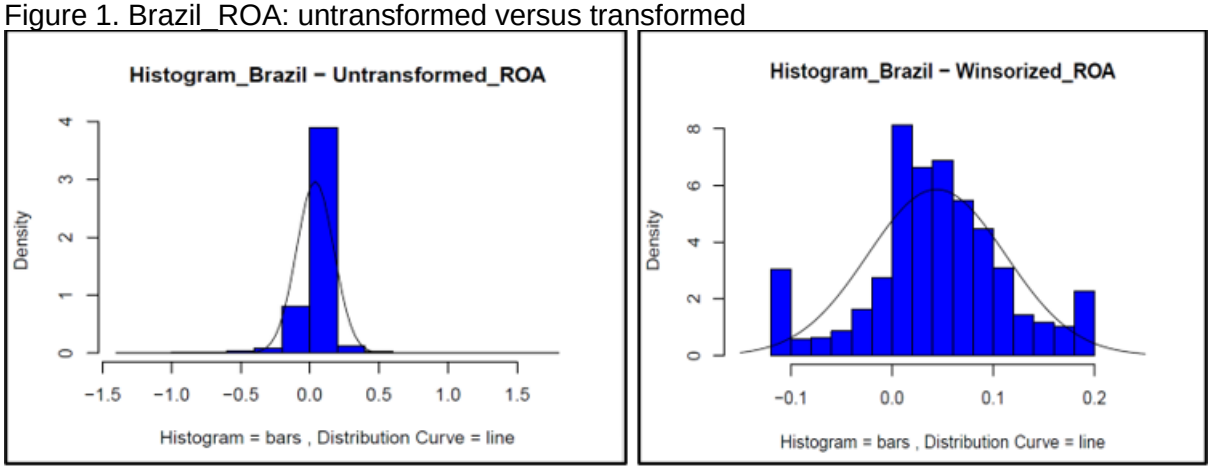


Figure 2. Brazil_ATO: untransformed versus transformed

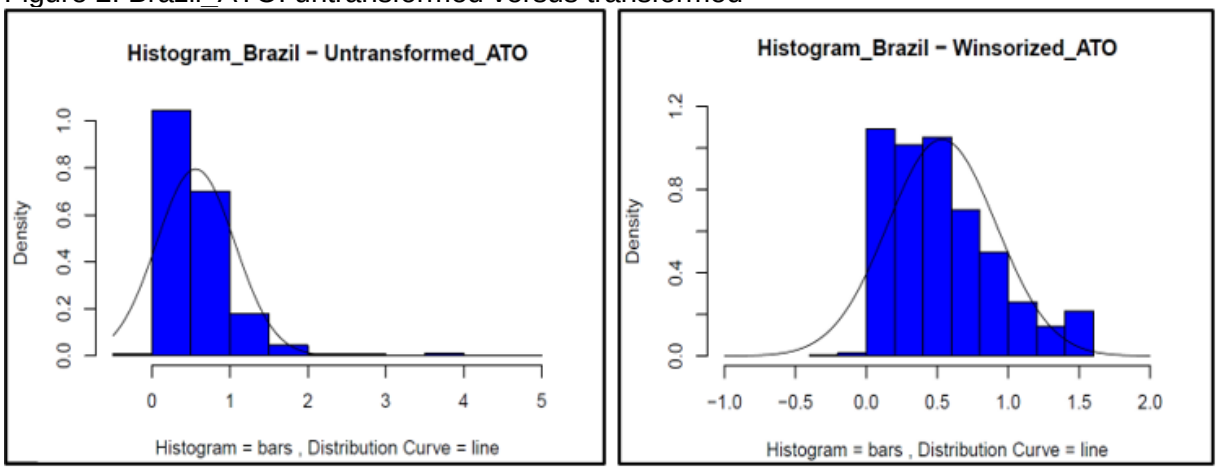


Figure 3. Brazil_MB: untransformed versus transformed

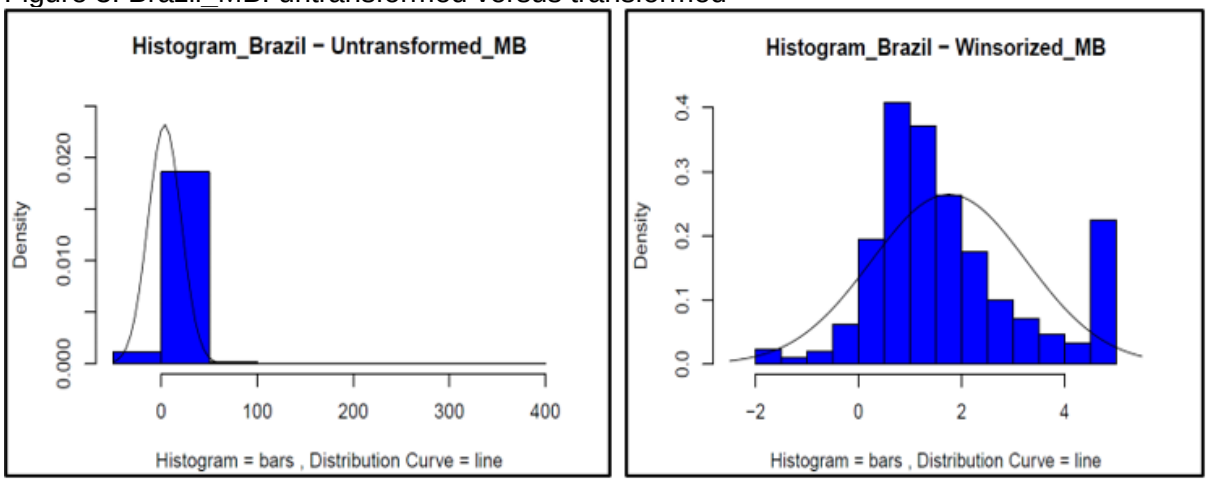


Figure 4. Indonesia_ROA: untransformed versus transformed

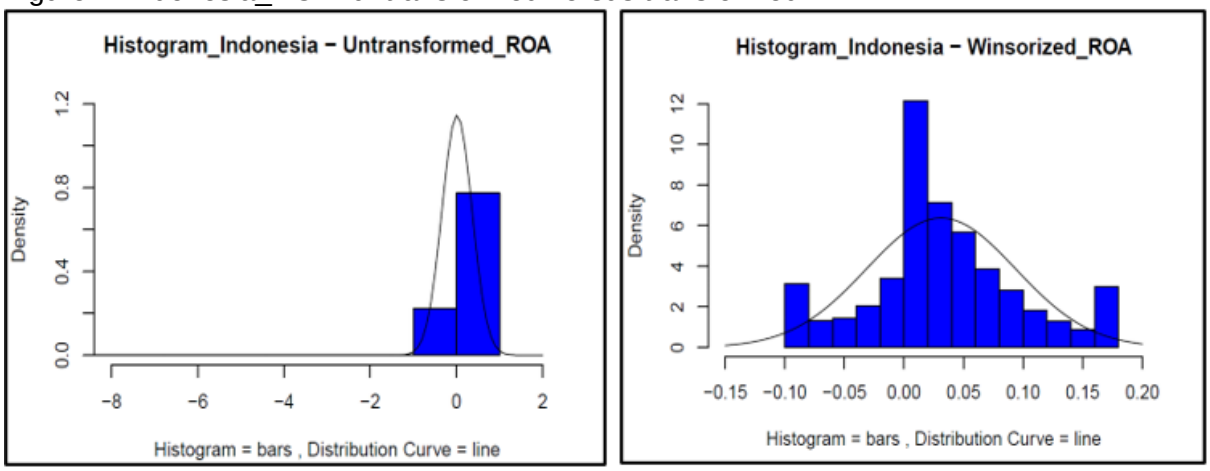


Figure 5. Indonesia_ATO: untransformed versus transformed

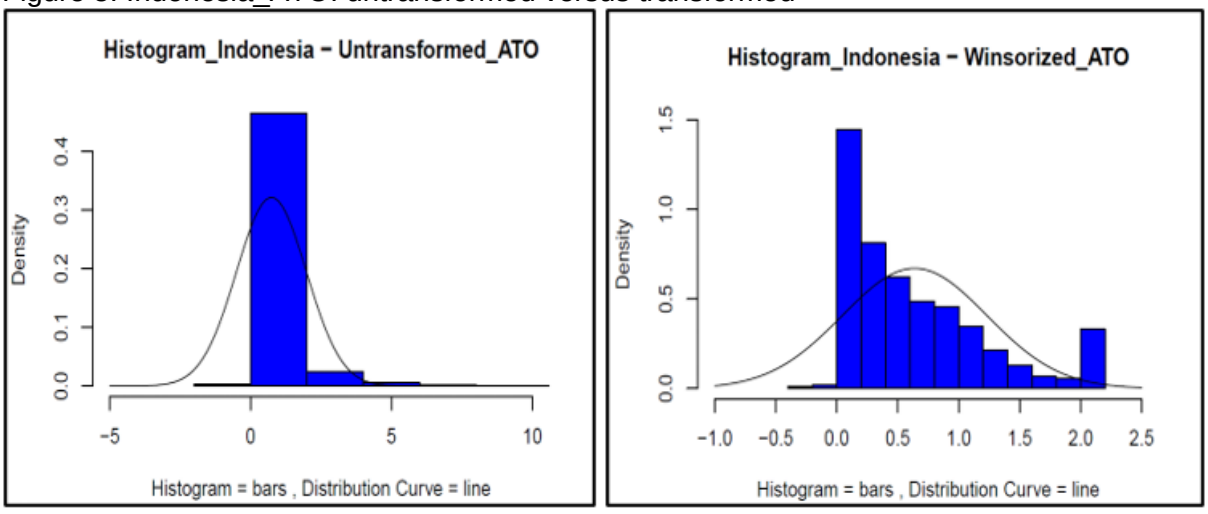


Figure 6. Indonesia_MB: untransformed versus transformed

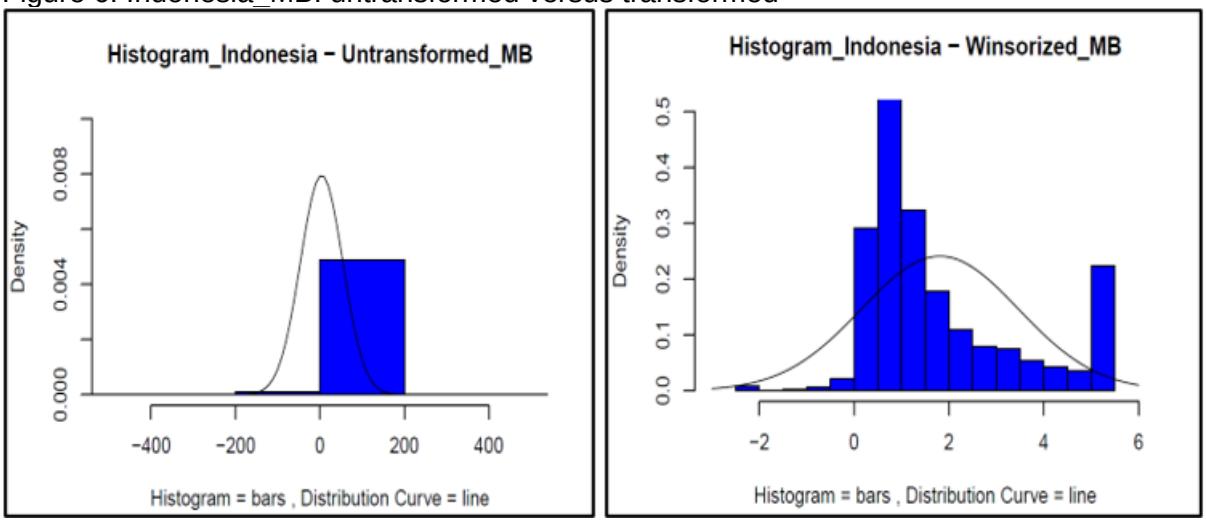


Figure 7. South Africa_ROA: untransformed versus transformed

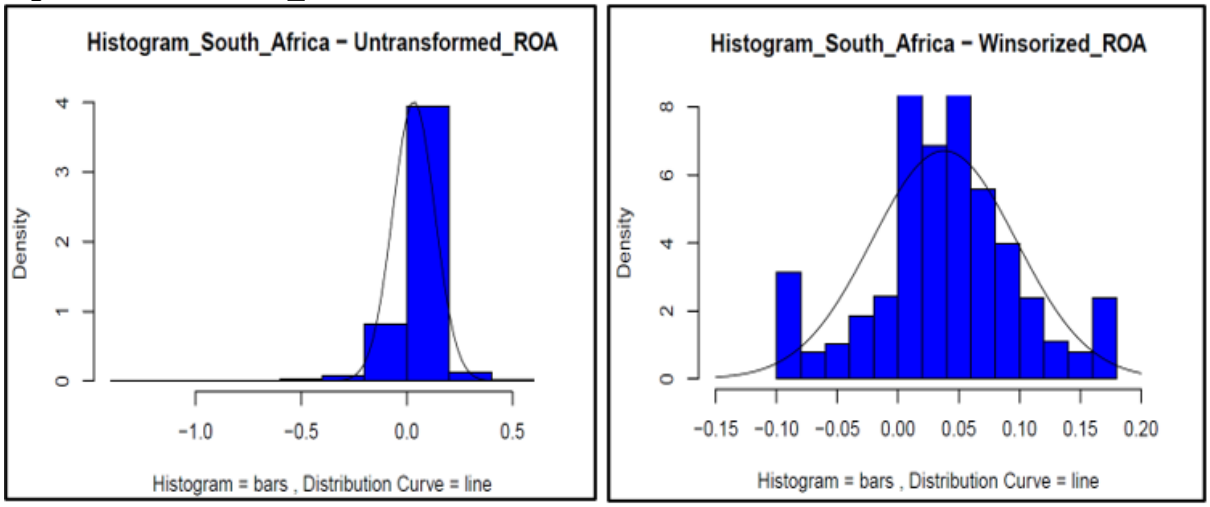


Figure 8. South Africa_ATO: untransformed versus transformed

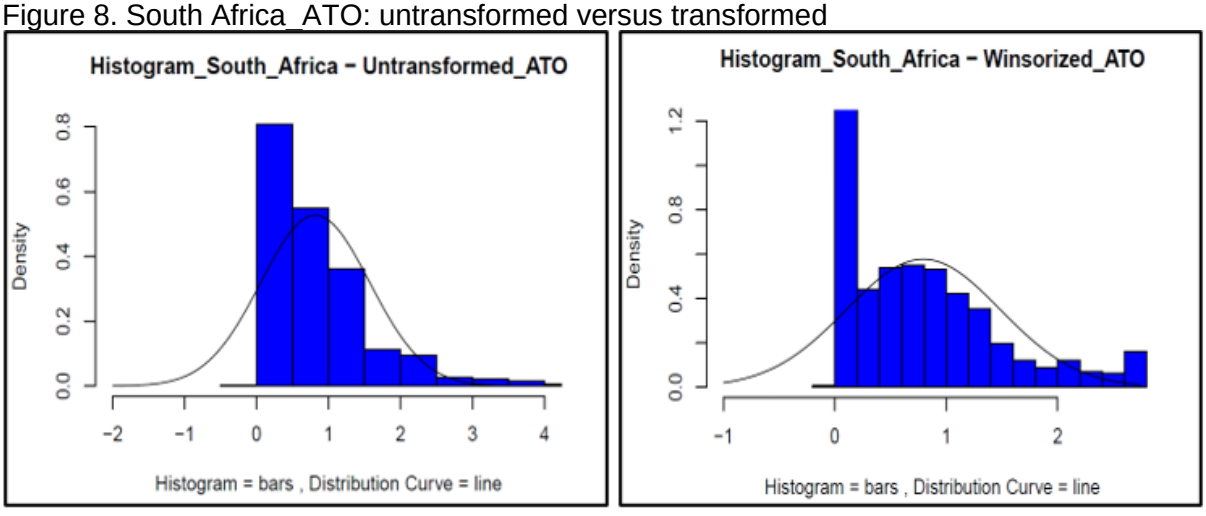
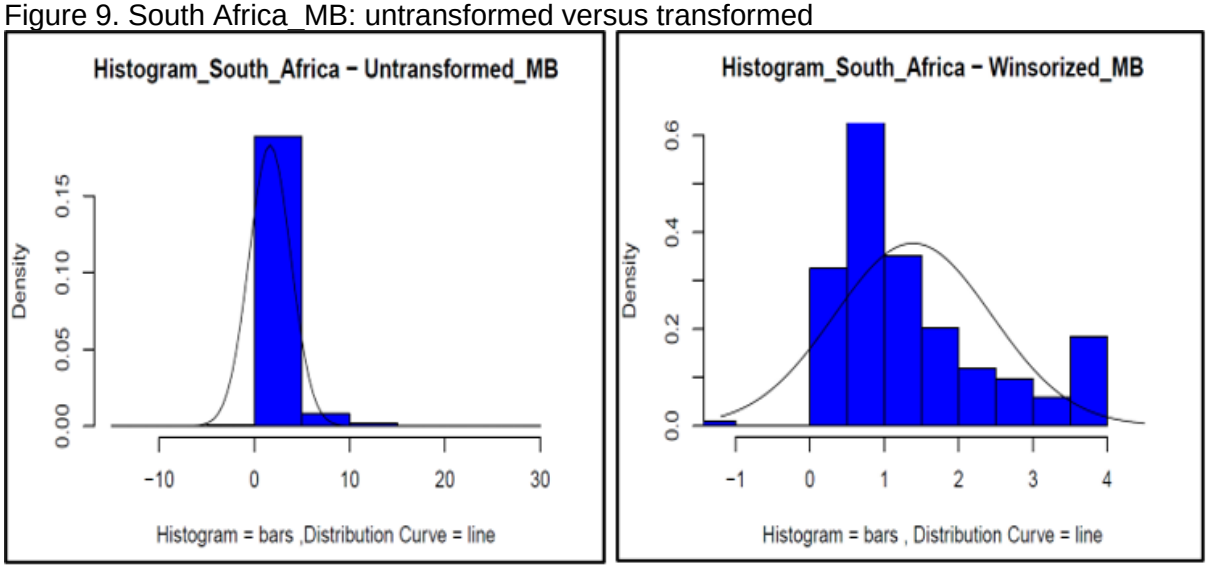


Figure 9. South Africa_MB: untransformed versus transformed



3.9 Regression Models

The regression models in equations 16 to 21 form the basis for analysing the relationships between the dependent and independent variables tested using the DGMM approach.

Model 1 (Hypotheses: $H_{1(a)}, H_{2(a)}, H_{3(a)}$)

$$ROA_{it} = \alpha + \beta_1 ROA_{t-1} + B_2 HCE_{it} + \beta_3 SCE_{it} + \beta_4 CEE_{it} + \beta_5 Lev\_ratio_{it} + \beta_6 Size_{it} + T.\lambda + \eta_i + \varepsilon_{it} \quad (16)$$

Model 2 (Hypotheses: $H_{1(b)}, H_{2(b)}, H_{3(b)}$)

$$ATO_{it} = \alpha + \beta_1 ATO_{t-1} + B_2 HCE_{it} + \beta_3 SCE_{it} + \beta_4 CEE_{it} + \beta_5 Lev\_ratio_{it} + \beta_6 Size_{it} + T.\lambda + \eta_i + \varepsilon_{it} \quad (17)$$

Model 3 (Hypotheses: $H_{1(c)}, H_{2(c)}, H_{3(c)}$)

$$MB_{it} = \alpha + \beta_1 \mathrm{MB_{t-1}} + \mathrm{B_2 HCE_{it}} + \beta_3 \mathrm{SCE_{it}} + \beta_4 \mathrm{CEE_{it}} + \beta_5 \mathrm{Lev\_ratio_{it}} + \beta_6 \mathrm{Size_{it}} + \mathrm{T.\lambda} + \eta_i + \varepsilon_{it} \quad (18)$$

Model 4 (Hypotheses: $\mathrm{H_{4(a)}}$)

$$\mathrm{ROA_{it}} = \alpha + \beta_1 \mathrm{ROA_{t-1}} + \mathrm{B_2 VAIC™_{it}} + \beta_5 \mathrm{Lev\_ratio_{it}} + \beta_6 \mathrm{Size_{it}} + \mathrm{T.\lambda} + \eta_i + \varepsilon_{it} \quad (19)$$

Model 5 (Hypotheses: $\mathrm{H_{4(b)}}$)

$$\mathrm{ATO_{it}} = \alpha + \beta_1 \mathrm{ATO_{t-1}} + \mathrm{B_2 VAIC™_{it}} + \beta_5 \mathrm{Lev\_ratio_{it}} + \beta_6 \mathrm{Size_{it}} + \mathrm{T.\lambda} + \eta_i + \varepsilon_{it} \quad (20)$$

Model 6 (Hypotheses: $\mathrm{H_{4(c)}}$)

$$\mathrm{MB_{it}} = \alpha + \beta_1 \mathrm{MB_{t-1}} + \mathrm{B_2 VAIC™_{it}} + \beta_5 \mathrm{Lev\_ratio_{it}} + \beta_6 \mathrm{Size_{it}} + \mathrm{T.\lambda} + \eta_i + \varepsilon_{it} \quad (21)$$

3.10 Diagnostic Tests

Various diagnostic tests were performed to ensure the reliability of the regressions and the resultant inferences.

Multicollinearity between the explanatory variables result in biased coefficient estimation and negatively impacts the explanatory power of the regression model (Yoo et al., 2014). HCE and SCE has the greatest probability of displaying multicollinearity. Consequently, it is important that the covariance between the independent variables must be tested to establish that no correlation exists between the predictive variables. Pairwise **Pearson correlation** and **Variance Inflation Factor (VIF)** tests were conducted to establish the absence of multicollinearity.

The Pearson correlation formula is expressed as follow (Wegner, 2012):

$$r = \frac{n\sum xy - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x)^2] * [n\sum y^2 - (\sum y)^2]}} \quad (22)$$

Where:

r = the sample correlation coefficient

x = the value of the independent variable

y = the value of the dependent variable

n = the number of paired data points in the sample.

The result of the correlation ranges from -1 to +1, where -1 depicts a perfect negative correlation and +1 a perfect positive correlation. A value of zero (0) depicts no correlation (Wegner, 2012).

The VIF reflects the extent to which the slope of the explanatory variables increases due to multicollinearity (Thompson, et al., 2017). A high VIF suggests a dependence between the explanatory variables. Maji and Goswami (2016) postulates that the VIF in excess of 10 and a Pearson correlation of 0.8 indicates the presence of multicollinearity. It is noteworthy to mention that this study seeks to observe the relationship between the dependent and independent variables and not to predict the direction.

The expression of the VIF is (Thompson, et al., 2017):

$$\mathrm{VIF_i} = \frac{1}{1-\mathrm{R^2}} \quad (23)$$

Where:

R^2 = multiple correlation coefficient

We applied the **Augmented Dickey-Fuller** test (**ADF**) to establish whether the time series is **stationary** or has a **unit root**. ADF is an important and common statistical test to avoid spurious results in the presence of unit root. The presence of unit root suggests that the time series is non-stationary. If the unit root is present, the stability or reliability of the model could be impacted. If the time series is stationary, the mean and variance is constant over time which is important for reliability of the time series analysis (Baltagi, 2005; Wooldridge, 2016).

When **heteroskedasticity** is present in a regression, the error term in the panel model is not constant, in other words it is not homoskedastic (Wooldridge, 2016). Nadeem (2016) suggests that there are various reasons for the presence of heteroskedasticity, e.g. too many or too few variables**.** Similarly, evidence of **serial correlation or autocorrelation** in the error term of a multiple regression suggests that a variable is correlated with past values. When the properties of OLS are violated, homoskedasticity of the regression and no serial correlation, the coefficients of the regression is not considered to be best linear unbiased estimate (BLUE). To test for the presence or violation of properties, we employed the **Breusch-Pagen** and **Wooldridge tests** in R studio.

Endogeneity refers to a concept in econometrics where an explanatory variable is correlated with the error term in a regression model. This correlation can lead to bias and inconsistent coefficients making it challenging to infer casual relationships. Wooldridge (2016) postulates that endogeneity is caused in one of three ways. Firstly, due to omitted variables which is caused by the unavailability of a variable e.g. data regarding research and development. Secondly, as a result of a measurement error and finally, due to simultaneity. Simultaneity occurs when the dependent variable impacts the independent variable and vice versa, resulting in a bi-directional or reverse causality relationship (Wooldridge, 2016; Bhattu-Babajee and Seetanah, 2022).

We followed the Arellano-Bond difference GMM approach as suggested by Nadeem et al. (2019) to deal with endogeneity, the presence of heteroskedasticity and serial correlation (Baum et al., 2003).

The statistical test namely, **Sargan Test including robust standard errors**, was calculated via R Studio. The Sargan test is used to assess the validity of the instrumental variables (IV) in a regression model by ensuring that there is no correlation between the error term and the

instruments (Baum et al., 2003; Wooldridge, 2010). Rejecting the null hypothesis would suggest that the instruments used on the model is invalid and that the IVs may be biased. In other words, the p-value of the test statistic will be significant.

First-order autocorrelation [AR (1)] and second-order autocorrelation [AR (2)] diagnostic tests were used to establish the presence of serial correlation in the error terms of dynamic models such as the difference GMM. These tests determine the validity of the instruments used in the GMM process. First-order autocorrelation does not invalidate the use of lag variables as instruments (Arellano and Bond, 1991; Roodman, 2009b; Wooldridge, 2010). However, it is critical that the null hypothesis for AR (2) is not rejected. In other words, the p-value must be statistically not significant to ensure the reliability and validity of the GMM estimator.

Finally, Roodman (2009b) and Nadeem et al. (2017) postulate that researchers must report the **instrument count** as well as the **number of groups.** Validity of the instruments can also be confirmed where the number of instruments is less than the number of groups.

3.11 Summary and Conclusion

Chapter 3 outlined the data analysis process that will be followed and provided the reasoning for the data selection as well as the period. The data was assessed and transformed to account for outliers. Moreover, we outlined the various regression models and equations. The chapter detailed the various diagnostic tests that will be performed during this study to ensure data integrity.

In Chapter 4, we discuss the results of the descriptive statistics, various diagnostic tests and regression models.

CHAPTER 4: RESULTS AND DISCUSSION

In Chapter 4, we will analyse the data and interpret the results. We start by discussing descriptive statistics. Then, we will analyse the various diagnostic tests and regression models postulated. We will end the chapter with a summary of the findings.

4.1 Descriptive Statistics

In Chapter 3, we outlined the process and discussed how we dealt with outliers in the data set. Table 7 depicts the descriptive statistics for the countries and the various outputs insofar as the minimum, maximum, median, mean, and standard deviation values are concerned. The salient observations are highlighted below.

We observe the untransformed data with high standard deviation values around the mean for most variables across the countries. Moreover, as noted in the histograms the previous chapter, the transformed data shows positive skewness.

Indonesia generates less ROA than Brazil and South Africa on average. Indonesia's leverage ratio is also lower than Brazil and South Africa. We can deduce that Indonesian firms are debt averse and more reliant on growing shareholder value by making use of internally generated funds and or equity funding. Furthermore, Indonesian firms are less efficient in utilising their physical assets, expensing innovation capital hence driving down profitability in the near term of which the benefit will only be seen in future, suggesting a lagging effect. Moreover, the weak ROA performance could be due to lack of investment in technology. The result contradicted Soetanto and Liem (2019), which showed a higher mean ROA of 11.414%.

South Africa has the lowest untransformed MB. However, the transformed MB score of South Africa and Indonesia aligns with previous studies of Firer and Mitchell Williams (2003) and Nimtrakoon (2015). The MB value for Brazil and South Africa is lower than what has been reported by Nadeem et al. (2017). The transformed mean MB scores between the three countries exhibit similar values in a narrow range.

South Africa displays the lowest transformed mean VAIC™ score and the highest transformed mean physical capital score. This suggests that relative to Brazil and Indonesia, South African businesses still favour tangible asset accumulation above IC to drive performance and firm valuation.

Table 7. Descriptive Statistics

Untransformed						
Brazil	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA	1040	-1,358	1,670	0,043	0,040	0,135
ATO	1040	-0,283	4,504	0,479	0,561	0,502
MB	1040	-43,821	373,892	1,372	3,556	17,175
HCE	1040	-17,711	714,171	2,381	4,874	23,765
SCE	1040	-10,335	159,553	0,618	0,852	5,137
CEE	1040	-50,942	46,272	0,440	0,569	2,943
VAIC™	1040	-49,691	715,287	3,599	6,296	24,484
Lev_ratio	1040	-197,396	398,556	1,130	3,112	18,032
Size	1040	5,406	20,929	13,537	13,410	2,168
Indonesia	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA	2115	-9,498	0,686	0,024	0,013	0,348
ATO	2115	-0,285	28,824	0,458	0,740	1,241
MB	2115	-1848,308	648,531	1,155	3,962	50,122
HCE	2115	-74,665	228,697	2,716	3,925	7,579
SCE	2115	-105,961	161,375	0,668	0,597	5,185
CEE	2115	-49,461	96,268	0,256	0,406	2,571
VAIC™	2115	-105,952	230,157	3,832	4,928	9,663
Lev_ratio	2115	-598,445	190,307	0,702	1,300	14,412
Size	2115	6,813	20,856	12,088	12,305	1,722
South Africa	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA	780	-1,207	0,533	0,039	0,033	0,099
ATO	780	-0,088	4,447	0,670	0,814	0,756
MB	780	-11,223	27,801	1,006	1,633	2,179
HCE	780	-40,553	347,814	1,967	8,810	32,590
SCE	780	-4,164	19,895	0,510	0,570	0,900
CEE	780	-9,126	57,491	0,515	0,752	2,450
VAIC™	780	-41,568	349,197	3,233	10,132	32,684
Lev_ratio	780	-28,289	89,230	0,897	2,548	7,042
Size	780	8,974	19,206	13,114	13,349	2,019

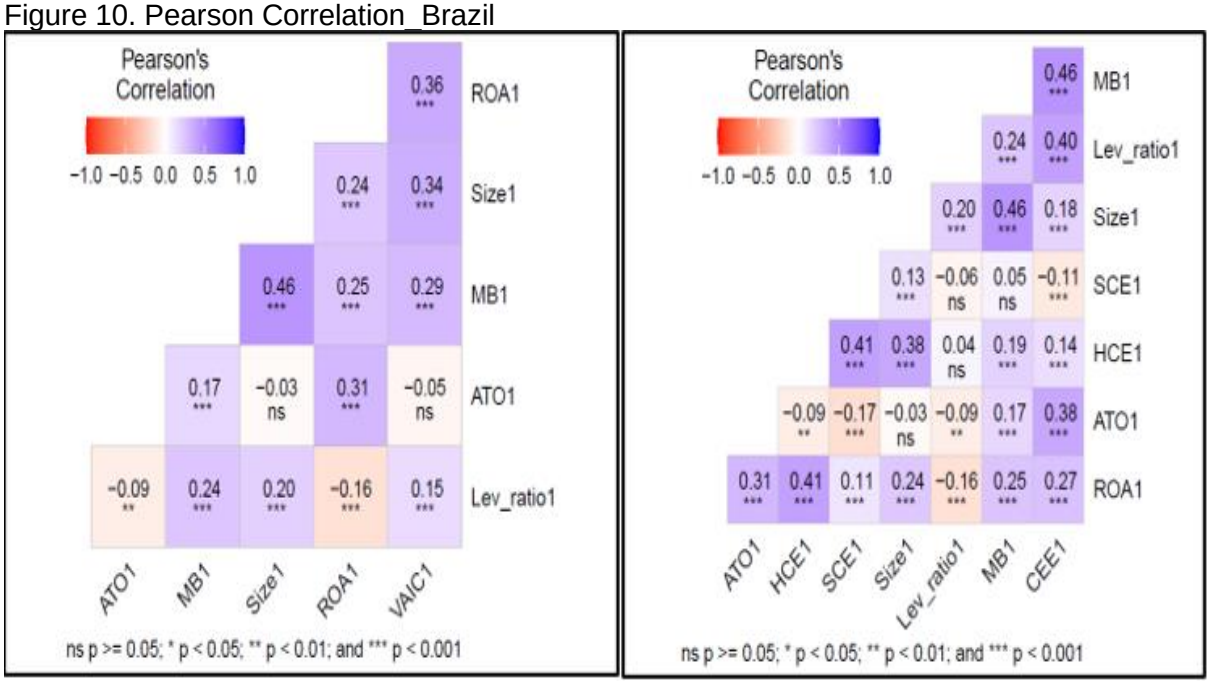
Winsorized						
Brazil	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA1	1040	-0,100	0,192	0,043	0,044	0,068
ATO1	1040	-0,283	1,522	0,479	0,533	0,383
MB1	1040	-1,743	4,898	1,372	1,752	1,508
HCE1	1040	-3,057	9,461	2,381	3,391	2,855
SCE1	1040	-0,152	1,410	0,618	0,623	0,296
CEE1	1040	-0,453	1,402	0,440	0,491	0,394
VAIC1	1040	-2,958	12,025	3,599	4,663	3,426
Lev_ratio1	1040	-1,982	4,976	1,130	1,644	1,651
Size1	1040	7,650	19,294	13,537	13,419	2,121
Indonesia	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA1	2115	-0,095	0,162	0,024	0,031	0,063
ATO1	2115	-0,285	2,134	0,459	0,638	0,594
MB1	2115	-2,188	5,369	1,155	1,809	1,656
HCE1	2115	-2,714	9,140	2,716	3,384	2,606
SCE1	2115	-0,032	1,324	0,668	0,635	0,285
CEE1	2115	-0,353	0,909	0,256	0,301	0,258
VAIC1	2115	-2,512	11,132	3,832	4,456	3,056
Lev_ratio1	2115	-1,377	3,209	0,702	1,057	1,040
Size1	2115	7,821	16,659	12,088	12,288	1,666
South Africa	**Obs**	**Min**	**Max**	**Median**	**Mean**	**Stdev**
ROA1	780	-0,089	0,165	0,039	0,038	0,059
ATO1	780	-0,088	2,677	0,670	0,794	0,691
MB1	780	-1,231	3,733	1,006	1,386	1,058
HCE1	780	-1,594	6,746	1,967	2,846	2,103
SCE1	780	-0,232	1,350	0,510	0,546	0,296
CEE1	780	-0,546	1,621	0,515	0,584	0,452
VAIC1	780	-1,467	9,332	3,233	4,283	2,735
Lev_ratio1	780	-1,163	3,344	0,897	1,276	1,031
Size1	780	8,974	18,914	13,114	13,348	2,017

Source: own calculations

4.2 Multicollinearity

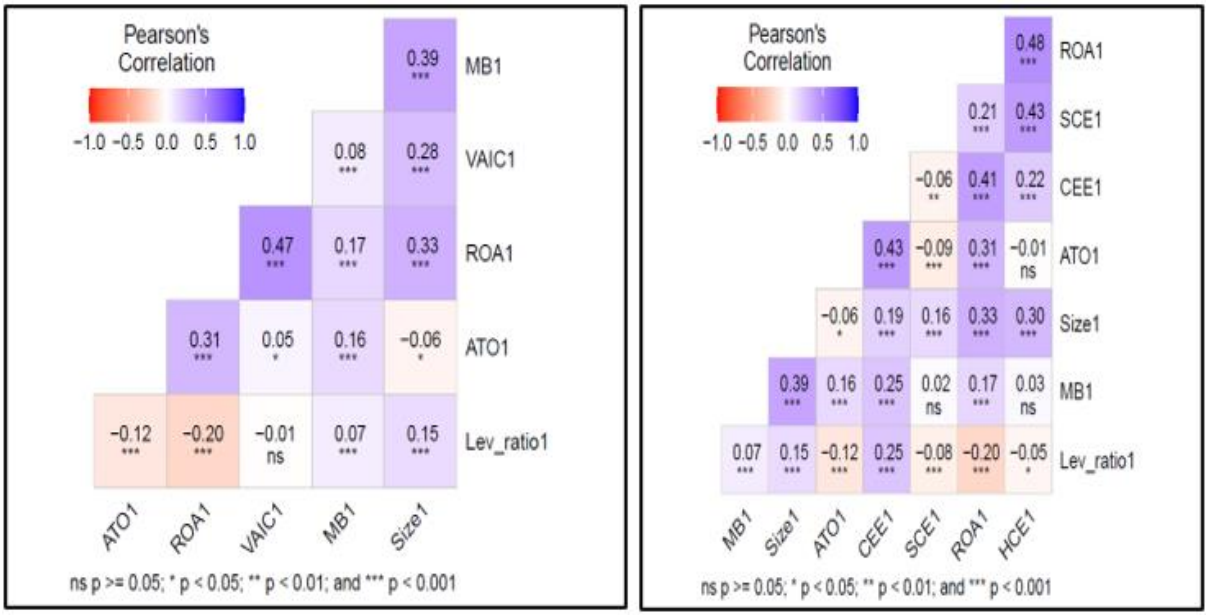
Maji and Goswami (2016) suggest that a correlation coefficient of less than 0.8 indicates the absence of excessive multicollinearity between independent variables. Figures 10 to 12 illustrate the results of the Pearson correlation between independent variables for Brazil, Indonesia and South Africa. We do not observe a concern for all countries with excessive multicollinearity, evidenced by the independent variables having a correlation coefficient lower than 0.8.

Figure 10. Pearson Correlation_Brazil



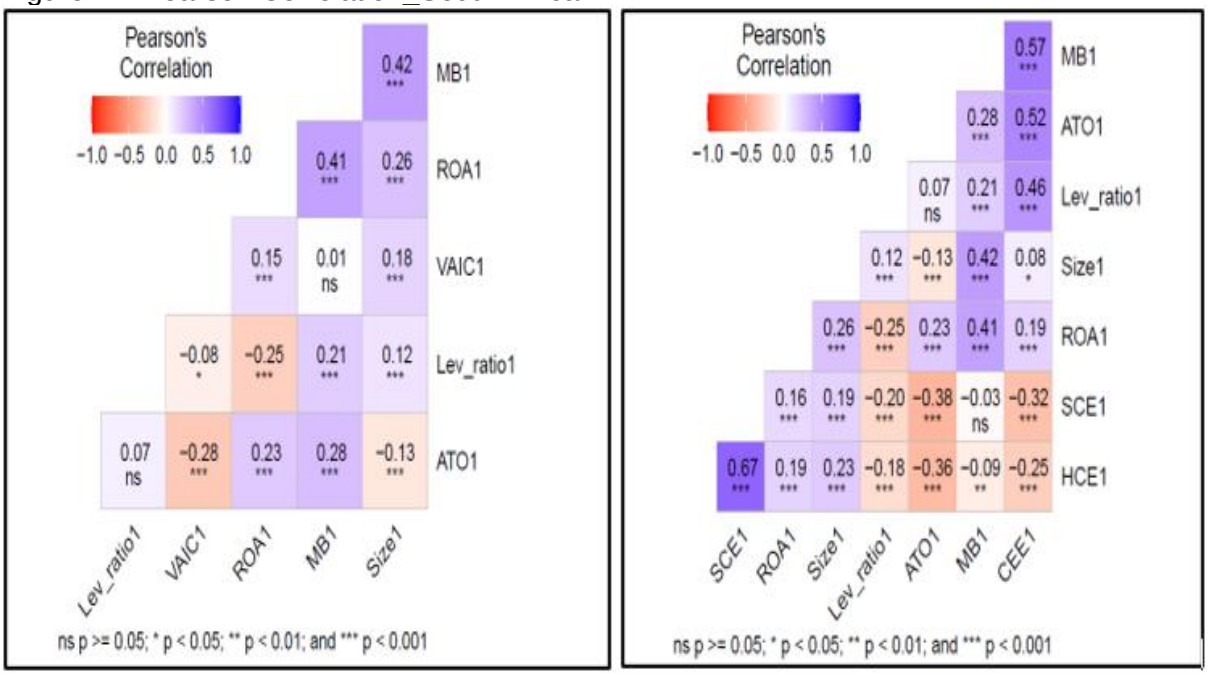
Source: own calculations

Figure 11. Pearson Correlation_Indonesia



Source: own calculations

Figure 12. Pearson Correlation_South Africa



Source: own calculations

4.3 Variance Inflation Factor (VIF)

A VIF greater than ten suggests excessive multicollinearity between independent variables. We ran VIF tests on both the static and dynamic OLS models. We note in Table 8 that in all instances, the VIF values are below two, suggesting that no excessive collinearity exists between the independent variables. These findings support the Pearson correlation test results. The largest VIF value was 1.704 across all the variables for the static OLS and 1.768 for the dynamic OLS regression.

Table 8. VIF Results

		Brazil		Indonesia		South Africa	
D.Var	I.Var	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS
ROA1	ROA1_lag		1,157		1,230		1,200
	HCE1	1,344	1,366	1,264	1,291	1,704	1,768
	SCE1	1,150	1,143	1,139	1,145	1,413	1,439
	CEE1	1,213	1,223	1,224	1,273	1,417	1,444
	VAIC™1	1,214	1,246	1,125	1,175	1,410	1,435
D.Var	I.Var	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS
ATO1	ATO1_lag		1,312		1,361		1,527
	HCE1	1,344	1,319	1,264	1,264	1,704	1,749
	SCE1	1,150	1,151	1,139	1,144	1,413	1,459
	CEE1	1,213	1,257	1,224	1,277	1,417	1,488
	VAIC™1	1,214	1,203	1,125	1,122	1,410	1,415
D.Var	I.Var	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS	Static OLS	Dynamic OLS
MB1	MB_lag		1,208		1,103		1,414
	HCE1	1,344	1,323	1,264	1,265	1,704	1,756
	SCE1	1,150	1,146	1,139	1,143	1,413	1,458
	CEE1	1,213	1,258	1,224	1,230	1,417	1,631
	VAIC™1	1,214	1,219	1,125	1,122	1,410	1,434

Source: own calculations

4.4 Unit Root and Stationarity

The Augmented Dickey-Fuller test was conducted to check for the presence of unit root and stationarity of the time series. The results across all the variables indicated that the time series is stationary; therefore, the null hypothesis was rejected at the 5% confidence level for the presence of unit root. Consequently, we are comfortable that the models will be stable and reliable, which could otherwise lead to spurious results.

Table 9. ADF Results

		ROA	ATO	MB	HCE	SCE	CEE	VAIC™	LEV	SIZE
Country	**Statistic**	-8,182	-7,484	-8,718	-7,565	-8,482	-7,799	-7,625	-7,350	-9,024
Brazil	***P*-Value**	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Lag Order	10	10	10	10	10	10	10	10	10
	Unit Root (Y/N)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country	**Statistic**	-12,081	-9,519	-10,729	-11,858	-11,674	-11,165	-11,585	-11,226	-10,541
Indonesia	***P*-Value**	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Lag Order	12	12	12	12	12	12	12	12	12
	Unit Root (Y/N)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country	**Statistic**	-8,530	-8,718	-8,665	-7,897	-7,841	-8,053	-7,890	-6,014	-7,953
South Africa	***P*-Value**	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Lag Order	9	9	9	9	9	9	9	9	9
	Unit Root (Y/N)	Y	Y	Y	Y	Y	Y	Y	Y	Y

Source: own calculations

4.5 Heteroskedasticity and Autocorrelation

The Breusch-Pagan test (BP test) for heteroskedasticity in Table 10 rejects the null hypothesis of homoscedasticity. In all instances the p-values were significant; below the 5% confidence level. Similarly, the Wooldridge test (W test) for autocorrelation in Table 11 was performed. The results are mixed, as noted in the table below. Five models accepted the null hypothesis for the presence of serial correlation where the p-value is above the 5% confidence level. These concerns will be addressed in the DGMM model (Roodman, 2009b).

Table 10. Breusch-Pagan Test

BP Test	Statistic (p-value)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Brazil	**Test statistic**	89,781	43,872	61,919	112,340	26,654	26,183
	***P*-value**	0,000	0,000	0,000	0,000	0,001	0,001
Indonesia	**Test statistic**	123,330	71,550	69,179	115,080	36,627	37,969
	***P*-value**	0,000	0,000	0,000	0,000	0,000	0,000
South Africa	**Test statistic**	41,073	50,672	70,573	33,749	54,396	49,435
	***P*-value**	0,000	0,000	0,000	0,000	0,000	0,000

Source: own calculations

Table 11. Wooldridge Test

W Test	Statistic (p-value)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Brazil	**Test statistic**	1,293	39,405	30,489	0,910	39,053	29,950
	***P*-value**	0,256	0,000	0,000	0,341	0,000	0,000
Indonesia	**Test statistic**	25,143	7,719	4,095	21,967	9,977	2,523
	***P*-value**	0,000	0,006	0,043	0,000	0,002	0,112
South Africa	**Test statistic**	0,481	16,110	8,673	0,702	16,272	14,245
	***P*-value**	0,488	0,000	0,003	0,402	0,000	0,000

Source: own calculations

4.6 Regression Models

In the following section we analyse the various DGMM regressions as well as Arellano-Bond test static results. We assess the robustness of the DGMM against the dynamic OLS and round off the section with an interpretation of the findings.

The statistical significance in the tables 12 – 29 are represented as follows:

Where:

*** = 0.1%

** = 1%

* = 5%

. = 10%

NS = not statistically significant

4.6.1 Brazil: Results

All the independent variables and the lagged regressor of **models 1** (Table 12) **and 4** (Table 13) had a positive relationship with ROA. However, the strength of the statistical significance varied. For example, ROA1_lag and VAIC™ were significant at a 5% level, HCE and CEE at a 1% level and SCE at a 10% level. The result supports the findings of Chen et al. (2005), Nadeem et al. (2017), Nadeem et al. (2018) but contradicts Firer and Mitchell Williams (2003) including Smriti and Das (2018). Firer and Mitchell Williams (2003) found no relationship between ROA and HCE, nor did they find a relationship between ROA and CEE. Smriti and Das (2018) on the other hand found no relationship between ROA and HCE in addition to ROA and SCE. Size plays a positive and statistically significant role at the 5% level in terms of the returns firms generate in Brazil, by utilising both IC and physical capital. Consequently, we accept hypotheses $H_{1(a)}$, $H_{2(a)}$, $H_{3(a)}$, and $H_{4(a)}$, which state that VAIC™ and its individual components have a positive relationship with ROA.

Table 12. Brazil_Regression_Model 1

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
1	ROA1_lag	0,3523	0,1696	0,0378	*	AR1	-3,0359	0,0024	**
	HCE1	0,0087	0,0033	0,0086	**	AR2	-1,5413	0,1233	NS
	SCE1	0,0314	0,0167	0,0598	.	Sargan Test	1,0076	0,3155	NS
Brazil	CEE1	0,0595	0,0182	0,0011	**	Wald Test	100,0942	0,0000	***
	Lev_ratio1	-0,0037	0,0022	0,0866	.	#Instruments	30		
	Size1	0,0097	0,0049	0,0473	*	#Groups	208		
						#Obs	624		

Source: own calculations

Table 13. Brazil_Regression_Model 4

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
4	ROA1_lag	0,4518	0,2286	0,0481	*	AR1	-2,8748	0,0040	**
	VAIC™$_1$	0,0059	0,0027	0,0299	*	AR2	-1,3075	0,1910	NS
	Lev_ratio1	-0,0035	0,0023	0,1399	NS	Sargan Test	1,1083	0,2925	NS
Brazil	Size1	0,0121	0,0052	0,0207	*	Wald test	45,8232	0,0000	***
						#Instruments	24		
						#Groups	208		
						#Obs	624		

Source: own calculations

Models 2 (Table 14) **and 5** (Table 15) demonstrate no statistical evidence of a relationship between ATO and its lagged regressor, HCE and SCE but reflect a positive relationship with CEE and VAIC™ at the 5% level. The result is partially supported by Xu and Liu (2020), who found no statistical relationship between ATO and the independent variables HCE and SCE but found a positive relationship between ATO and CEE. Firer and Mitchell Williams (2003), including Smriti and Das (2018), on the other hand, found a positive relationship between ATO and HCE, ATO and SCE, as well as ATO and VAIC™. Moreover, Smriti and Das (2018) found a negative relationship between ATO and CEE. Xu and Li (2022) found a positive relationship between ATO and the independent variables, apart from the negative relationship between ATO and HCE. Given these findings, we found mixed support for our hypotheses. We reject hypotheses $H_{1(b)}$, $H_{2(b)}$ given that no positive relationship is observed between ATO, HCE and SCE but accept $H_{3(b)}$ and $H_{4(b)}$ which state that VAIC™ and CEE have a positive relationship with ATO.

Table 14. Brazil_Regression_Model 2

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
2	ATO1_lag	0,0718	0,1773	0,6856	NS	AR1	-0,5459	0,5851	NS
	HCE1	0,0061	0,0062	0,3181	NS	AR2	-3,4908	0,0005	***
	SCE1	0,0421	0,0397	0,2889	NS	Sargan Test	1,4650	0,2261	NS
Brazil	CEE1	0,1327	0,0481	0,0058	**	Wald Test	19,7319	0,0031	
	Lev_ratio1	-0,0030	0,0058	0,6030	NS	#Instruments	30		
	Size1	0,0096	0,0104	0,3575	NS	#Groups	208		
						#Obs	624		

Source: own calculations

Table 15. Brazil_Regression_Model 5

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
5	ATO1_lag	0,1146	0,1941	0,5550	NS	AR1	-0,5652	0,5719	NS
	VAIC™1	0,0079	0,0038	0,0362	*	AR2	-3,4861	0,0005	***
	Lev_ratio1	-0,0001	0,0059	0,9909	NS	Sargan Test	1,3914	0,2382	NS
Brazil	Size1	0,0128	0,0104	0,2191	NS	Wald Test	0,1100		
						#Instruments	24		
						#Groups	208		
						#Obs	624		

Source: own calculations

The result of **models 3** (Table 16) **and 6** (Table 17) is similar to models 2 and 5, apart from the relationship between the lagged regressor and MB. Similar results are demonstrated by Firer and Mitchell Williams (2003), Xu and Liu (2020) but contradict the findings of Nimtrakoon (2015), Nadeem et al. (2017) and Bhattu-Babajee and Seetanah (2022), who found a positive relationship between MB and the explanatory variables. We observe that the control variables are statistically significant in models 3 and 6; however, their influence appears stronger when VAIC™ is measured. We reject hypotheses $H_{1(c)\ and}$ $H_{2(c)}$ since no positive association is observed between MB, HCE and SCE but accept $H_{3(c)}$ and $H_{4(c),}$ which state that VAIC™ and CEE have a positive relationship with MB.

Table 16. Brazil_Regression_Model 3

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
3	MB1_lag	0,4349	0,0949	0,0000	***	AR1	-2,9393	0,0033	**
	HCE1	-0,0620	0,0409	0,1298	NS	AR2	0,2421	0,8087	NS
	SCE1	0,1711	0,2397	0,4755	NS	Sargan Test	0,1040	0,7470	NS
Brazil	CEE1	1,7575	0,2818	0,0000	***	Wald Test	228,7018	0,0000	***
	Lev_ratio1	0,0760	0,0415	0,0673	.	#Instruments	30		
	Size1	0,6242	0,0969	0,0000	***	#Groups	208		
						#Obs	624		

Source: own calculations

Table 17. Brazil_Regression_Model 6

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
6	MB1_lag	0,4483	0,0862	0,0000	***	AR1	-2,9461	0,0032	**
	VAIC™1	0,1288	0,0345	0,0002	***	AR2	0,2134	0,8310	NS
	Lev_ratio1	0,1204	0,0321	0,0002	***	Sargan Test	0,2040	0,6515	NS
Brazil	Size1	0,6211	0,1011	0,0000	***	Wald Test	159,0759		
						#Instruments	24		
						#Groups	208		
						#Obs	624		

Source: own calculations

4.6.2 Indonesia: Results

Models 1 (Table 18) **and 4** (Table 19) of Indonesia reflect similar results to Brazil's. The main difference is that Indonesia reflects a positive and very strong statistical significance between the explanatory variables and ROA, given the p-values of 0.1%. Moreover, SCE (model 1) and Lev_ratio (model 1 and 4) reflect no statistical significance for both models. The results align with the findings of Maji and Goswami (2016), Nimtrakoon (2015), Nadeem et al. (2017), Chen et al. (2005), and Soetanto and Liem (2019), who reported a positive relationship between all explanatory variables and ROA across all sectors. This supports our results, except that ROA and SCE show no explanatory power in model 1. Firer and Mitchell Williams (2003), Bhattu-Babajee and Seetanah (2022), as well as Olarewaju and Msomi (2021), found that ROA and CEE either had no explanatory power or showed a statistically negative relationship, which contradicts our findings. We accept hypotheses $H_{1(a),}$ $H_{3(a)}$ and $H_{4(a),}$ which state that ROA has a positive association with but reject $H_{2(a).}$

Table 18. Indonesia_Regression_Model 1

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
1	ROA1_lag	0,3864	0,0699	0,0000	***	AR1	-5,5345	0,0000	**
	HCE1	0,0120	0,0014	0,0000	***	AR2	-0,3578	0,7205	NS
Indonesia	SCE1	0,0105	0,0065	0,1067	NS	Sargan Test	0,5682	0,4510	NS
	CEE1	0,0527	0,0122	0,0000	***	Wald Test	290,8051	0,0000	***
	Lev_ratio1	-0,0005	0,0018	0,7848	NS	#Instruments	30		
	Size1	0,0062	0,0031	0,0441	*	#Groups	423		
						#Obs	1269		

Source: own calculations

Table 19. Indonesia_Regression_Model 4

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
4	ROA1_lag	0,5028	0,0761	0,0000	***	AR1	-5,8957	0,0000	**
	VAIC™$_1$	0,0089	0,0010	0,0000	***	AR2	-0,0765	0,9390	NS
Indonesia	Lev_ratio1	0,0060	0,0020	0,7641	NS	Sargan Test	0,5133	0,4737	NS
	Size1	0,0083	0,0033	0,0133	*	Wald test	218,6739	0,0000	***
						#Instruments	24		
						#Groups	423		
						#Obs	1269		

Source: own calculations

The explanatory power of the independent variables in **models 2** (Table 20) **and 5** (Table 21) is positive and statistically significant, albeit the strength of the relationship varies. For example, ATO and CEE have a very strong statistically significant relationship at a 0.1% level, whereas ATO and HCE only have a strong relationship at a 1% level. Interestingly, we found no evidence in research to support our findings of the relationship of ATO with the explanatory variables. Based on our observations, academics either contradict our findings entirely (Firer

and Mitchell Williams, 2003; Firer and Stainbank, 2003) or support them in part (Xu and Liu, 2020; Smriti and Das, 2018; Nadeem et al., 2017). Consequently, we accept hypotheses $H_{1(b)}$, $H_{2(b)}$, $H_{3(b)}$ and $H_{4(b)}$, which state that ATO has a positive association with VAIC™ and its components.

Table 20. Indonesia_Regression_Model 2

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
2	ATO1_lag	-0,0360	0,0969	0,7107	NS	AR1	0,5436	0,5867	NS
	HCE1	0,0100	0,0035	0,0047	**	AR2	-1,7274	0,0841	NS
Indonesia	SCE1	0,0287	0,0164	0,0794	.	Sargan Test	0,9783	0,3226	NS
	CEE1	0,2743	0,0569	0,0000	***	Wald Test	83,4533	0,0000	***
	Lev_ratio1	-0,0182	0,0066	0,0058	**	#Instruments	30		
	Size1	0,0135	0,0081	0,0956	.	#Groups	423		
						#Obs	1269		

Source: own calculations

Table 21. Indonesia_Regression_Model 5

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
5	ATO1_lag	-0,0135	0,1046	0,8970	NS	AR1	0,4371	0,6621	NS
	VAIC™$_1$	0,0161	0,0034	0,0000	***	AR2	-1,8174	0,0691	NS
Indonesia	Lev_ratio1	-0,0132	0,0060	0,0283	*	Sargan Test	1,0088	0,3152	NS
	Size1	0,0187	0,0085	0,0270	*	Wald Test	28,1847		
						#Instruments	24		
						#Groups	423		
						#Obs	1269		

Source: own calculations

Similar to ROA1_lag, MB1_lag is positive and statistically very strong in explaining the relationship with MB in **models 3** (Table 22) **and 6** (Table 23). It would suggest that past values of MB have a significant impact on the current value. In other words, the relationship is bidirectional. Furthermore, we observed evidence of a negative relationship between MB and HCE as well as a positive relationship between MB and CEE at the 5% confidence level. No statistical relationship is observed between MB and SCE, as well as MB and VAIC™. Our findings are supported by Firer and Mitchell Williams (2003), as well as by Firer and Stainbank (2003). However, contradictory findings were observed in the studies by Soetanto and Liem (2019), Xu and Liu (2020), Nimtrakoon (2015), Bhattu-Babajee and Seetanah (2022), Nadeem et al. (2017), and Smriti and Das (2018). For example, Nadeem et al. (2017), Bhattu-Babajee and Seetanah (2022), and Soetanto and Liem (2019) found a positive relationship between MB and HCE. In contrast, Xu and Liu (2020) and Smriti and Das (2018) found no relationship. While Soetanto and Liem (2019) and Xu and Liu (2020) support our findings on the relationship between MB and SCE, other studies found a positive relationship between these variables (Smriti and Das, 2018; Nadeem et al., 2017; Nimtrakoon, 2015). Soetanto and Liem (2019)

and Xu and Liu (2020) contradict our findings on the relationship between MB and CEE. Statistically, we observe a strong association between the control variables and MB at the 1% level, suggesting that size and leverage play a significant role in determining the market-to-book values of firms in Indonesia. Given these findings, we reject hypotheses $H_{2(c)}$ and $H_{4(c)}$ due to the lack of a statistically significant association, but we accept $H_{1(c)}$ and $H_{3(c)}$ based on the observed positive relationship between the variables.

Table 22. Indonesia_Regression_Model 3

Model	l.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
3	MB1_lag	0,2734	0,0773	0,0004	***	AR1	-3,5379	0,0004	***
	HCE1	-0,0851	0,0368	0,0208	*	AR2	0,1746	0,8611	NS
Indonesia	SCE1	0,0143	0,1732	0,9343	NS	Sargan Test	2,0159	0,1557	NS
	CEE1	1,5547	0,7858	0,0479	*	Wald Test	300,7265	0,0000	***
	Lev_ratio1	0,2085	0,0773	0,0070	**	#Instruments	30		
	Size1	1,1306	0,0939	0,0000	***	#Groups	423		
						#Obs	1269		

Source: own calculations

Table 23. Indonesia_Regression_Model 6

Model	l.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
6	MB1_lag	0,2559	0,0700	0,0003	***	AR1	-3,7452	0,0002	**
	VAIC™1	0,0198	0,0271	0,4642	NS	AR2	-0,3483	0,7276	NS
Indonesia	Lev_ratio1	0,2721	0,0885	0,0021	**	Sargan Test	0,5483	0,4590	NS
	Size1	1,1147	0,0958	0,0000	***	Wald Test	290,2720		
						#Instruments	24		
						#Groups	423		
						#Obs	1269		

Source: own calculations

4.6.3 South Africa: Results

We find weak evidence in **model 1** (Table 24) supporting a positive relationship between ROA and its lagged regressor at the 10% confidence level. Moreover, **model 4** (Table 25) provides strong evidence of a positive relationship between ROA and its lagged regressor at the 1% level. HCE and CEE show no statistically significant relationship with ROA, a finding supported by Firer and Mitchell Williams (2003). The relationship between ROA and SCE is moderate, with significance at the 5% confidence level. Leverage does not appear to have any statistically significant association with ROA. This pattern is also observed in Indonesia, while weak support is found for Brazil at the 10% level in model 1 (Table 12). VAIC™ shows statistical significance at the 5% level, corroborated by Firer and Stainbank (2003).

Overall, our findings are partially supported or contradicted by existing research. For instance, Nadeem et al. (2017) found no statistical relationship between ROA and HCE in the South

African market but identified a positive relationship between ROA and both CEE and VAIC™. Conversely, Morris (2015) found a positive and statistically significant relationship between ROA and HCE in the South African market. Olarewaju and Msomi (2021) found a positive relationship between ROA and HCE and ROA and VAIC™ in the SADC region, but a negative relationship between ROA and CEE. Although the association between ROA and the individual IC components in South Africa does not align with those in Indonesia or Brazil, our findings suggest that the composite IC measure, VAIC™, and its relationship with ROA — as well as ROA and its lagged regressor — are statistically significant at the 5% level. This indicates that South African firms, like those in other emerging markets, utilise intellectual and physical capital to generate shareholder returns. Consequently, we reject hypotheses $H_{1(a)}$ and $H_{3(a)}$ due to the lack of association between the variables, but we accept $H_{2(a)}$ and $H_{4(a)}$ based on the observed positive association.

Table 24. South Africa_Regression_Model 1

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
1 South Africa	ROA1_lag	0,2314	0,1300	0,0751	.	AR1	-3,6859	0,0002	***
	HCE1	0,0016	0,0228	0,9454	NS	AR2	1,7770	0,0756	NS
	SCE1	0,0681	0,0273	0,0127	*	Sargan Test	0,0631	0,8016	NS
	CEE1	0,0215	0,0625	0,7314	NS	Wald Test	63,0710	0,0000	***
	Lev_ratio1	0,0009	0,0044	0,8439	NS	#Instruments	30		
	Size1	0,0396	0,1033	0,0001	***	#Groups	156		
						#Obs	468		

Source: own calculations

Table 25. South Africa_Regression_Model 4

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
4 South Africa	ROA1_lag	0,2133	0,0673	0,0015	**	AR1	-4,9573	0,0000	***
	VAIC™$_1$	0,0088	0,0037	0,0161	*	AR2	1,8947	0,0581	NS
	Lev_ratio1	-0,0010	0,0041	0,8032	NS	Sargan Test	0,0178	0,8940	NS
	Size1	0,0433	0,0088	0,0000	***	Wald test	50,6967	0,0000	***
						#Instruments	24		
						#Groups	156		
						#Obs	468		

Source: own calculations

Similar to Brazil and Indonesia, no statistical support was observed for the relationship between ATO and its lagged regressor in **models 2** (Table 26) **and 5** (Table 27), suggesting that the past values do not influence current values. Furthermore, the result of ATO and the explanatory variables is similar to Brazil's. For example, the association between ATO, CEE, and VAIC™ is significant at the 5% level, while no association is observed between ATO and HCE, as well as between ATO and SCE. It suggests that, on a composite level, South African and Brazilian firms efficiently leverage intellectual capital and physical capital to enhance

operational performance. In contrast, firms in Indonesia appear to be more operationally efficient than their South African and Brazilian counterparts, as indicated by the positive association between the ATO and the individual components of intellectual capital. This suggests that firms in Indonesia are better able to utilise their employees' skills, knowledge, systems, and processes to generate increased revenue while ensuring the efficient use of company assets. We reject hypotheses $H_{1(b)}$, $H_{2(b)}$ due to the lack of association between the variables but accept $H_{3(b)}$ and $H_{4(b)}$.

Table 26. South Africa_Regression_Model 2

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
2 South Africa	ATO1_lag	-0,0038	0,1135	0,9734	NS	AR1	0,1062	0,9154	NS
	HCE1	0,0100	0,0145	0,4924	NS	AR2	-0,8047	0,4210	NS
	SCE1	0,0224	0,0518	0,6653	NS	Sargan Test	0,1632	0,6863	NS
	CEE1	0,1559	0,0716	0,0293	*	Wald Test	26,5619	0,0002	***
	Lev_ratio1	-0,0107	0,0108	0,3225	NS	#Instruments	30		
	Size1	0,0381	0,0219	0,0819	.	#Groups	156		
						#Obs	468		

Source: own calculations

Table 27. South Africa_Regression_Model 5

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
5 South Africa	ATO1_lag	-0,0309	0,1125	0,7834	NS	AR1	0,1821	0,8555	NS
	VAIC™$_1$	0,0239	0,0070	0,0007	***	AR2	0,9174	0,3590	NS
	Lev_ratio1	-0,0071	0,0104	0,4962	NS	Sargan Test	0,2745	0,6003	NS
	Size1	0,0397	0,0208	0,0562	.	Wald Test	23,4952		
						#Instruments	24		
						#Groups	156		
						#Obs	468		

Source: own calculations

We observe weak evidence at the 10% confidence level of a positive relationship between MB and MB1_lag in **model 3** (Table 28). The results of **models 3 and 6** (Table 29) demonstrate that the relationship between MB and HCE, as well as MB and SCE, is negative which implies that South African firms do not efficiently make use of their human capital to maximise shareholder value, or the market perceives that investment on technology, systems and processes will not translate into enhanced shareholder value. This negative association could arise from a misalignment or insufficient investment in the skills and knowledge required by the firm, the capabilities of its employees, and a current business cycle that fails to appeal to investors. An alternative observation is that there is a strong positive association between MB value and CEE, implying that South African firms prefer to invest in physical capital to maximise shareholder value. MB and HCE, including MB and CEE display a strong relationship at the 1% level compared to MB and SCE at the 10% confidence level. The result

is partially supported by Firer and Mitchell Williams (2003) and Firer and Stainbank (2003). Nadeem et al. (2017) found a positive relationship between MB and HCE, including MB and SCE, in the South African market, which contradicts our findings.

Similarly, Morris (2015) found a positive relationship between MB and HCE in South Africa. Moreover, analogous to Indonesia, we observed no association between MB value and VAIC™, which contradicts the findings for Brazil, where a positive and statistically significant association is observed between MB and VAIC™. Accordingly, we reject hypotheses $H_{1(c)}$, $H_{2(c)}$ and $H_{4(c)}$ but accept $H_{3(c)}$, which states that MB and CEE have a positive association.

Table 28. South Africa_Regression_Model 3

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
3 South Africa	MB1_lag	0,6111	0,3465	0,0778	.	AR1	-1,6681	0,0953	.
	HCE1	-0,5784	0,1903	0,0024	**	AR2	-0,0302	0,7623	NS
	SCE1	-0,4741	0,2457	0,0537	.	Sargan Test	1,2327	0,2669	NS
	CEE1	1,8734	0,5268	0,0004	***	Wald Test	95,4780	0,0000	***
	Lev_ratio1	-0,0097	0,0374	0,7951	NS	#Instruments	30		
	Size1	1,0119	0,1175	0,0000	***	#Groups	156		
						#Obs	468		

Source: own calculations

Table 29. South Africa_Regression_Model 6

Model	I.Var	Coeff	Std Err	P-Val	Sigf	Tests	Result	P-Val	Sigf
6 South Africa	MB1_lag	0,0378	0,4113	0,9268	NS	AR1	0,0031	0,9975	NS
	VAIC™$_1$	-0,0271	0,0358	0,4484	NS	AR2	-1,9444	0,0518	NS
	Lev_ratio1	0,0156	0,0514	0,7607	NS	Sargan Test	3,8053	0,0511	NS
	Size1	1,0637	0,4490	0,0178	*	Wald Test	16,4320	0,0025	**
						#Instruments	24		
						#Groups	156		
						#Obs	1269		

Source: own calculations

Table 30 provides a summary of the findings.

Where:

+ = positive and statistically significant

- = negative and statistically significant

NS = not statistically significant

Table 30. DGMM Summary

	Var (models)	ROA1_lag	ATO1_lag	MB1_lag	HCE1	SCE1	CEE1	VAIC™
Brazil	ROA1(1;4)	+			+	+	+	+
	ATO1(2;5)		NS		NS	NS	+	+
	MB1 (3;6)			+	NS	NS	+	+
	Var (models)	ROA1_lag	ATO1_lag	MB1_lag	HCE1	SCE1	CEE1	VAIC™
Indonesia	ROA1(1;4)	+			+	NS	+	+
	ATO1(2;5)		NS		+	+	+	+
	MB1 (3;6)			+	-	NS	+	NS
	Var (models)	ROA1_lag	ATO1_lag	MB1_lag	HCE1	SCE1	CEE1	VAIC™
South Africa	ROA1(1;4)	+			NS	+	NS	+
	ATO1(2;5)		NS		NS	NS	+	+
	MB1 (3;6)			+	-	-	+	NS

NS = Not Significant
+ = Positive and statistically signficant
- = Negative and statistically significant

Source: own calculations

4.7 Diagnostic tests and validity of results

We conducted the AR (1) and AR (2) tests and rejected the null hypothesis for AR (1) autocorrelation. However, in respect of AR (2) we fail to reject the null hypothesis. Therefore, no second-order autocorrelation in residuals exists, given that the p-value is above the conventional 5% confidence level (Roodman, 2009b; Nadeem et al.,2017). The models are appropriately specified given the validity of the instruments, which is further supported by the Sargan test that is above the 5% confidence level. Moreover, the number of instruments is less than the number of groups, which further endorses the validity of the models (Nadeem et al., 2017). The Wald test for coefficients is statistically significant, suggesting that the explanatory variables, including the lagged variable, are jointly significant. It also posits that the explanatory variables have a statistically significant impact on the dependent variable.

Table 31. DGMM Diagnostics Test Results

Brazil	AR(1)	AR(2)	Sargan Test	Wald Test	No. Inst	No. Obs	No. Groups
Model 1	0,0024	0,1233	0,3155	0,0000	30	624	208
Model 2	0,5851	0,0005	0,2261	0,0031			
Model 3	0,0033	0,8087	0,7470	0,0000			
Model 4	0,0040	0,1910	0,2925	0,0000			
Model 5	0,5719	0,0005	0,2382	0,1100			
Model 6	0,0032	0,8310	0,6515	0,0000			
Indonesia	AR(1)	AR(2)	Sargan Test	Wald Test	No. Inst	No. Obs	No. Groups
Model 1	0,0000	0,7205	0,4510	0,0000	30	1269	423
Model 2	0,5867	0,0841	0,3226	0,0000			
Model 3	0,0004	0,8611	0,1557	0,0000			
Model 4	0,0000	0,9390	0,4737	0,0000			
Model 5	0,6621	0,0691	0,3152	0,0000			
Model 6	0,0002	0,7276	0,4590	0,0000			
South Africa	AR(1)	AR(2)	Sargan Test	Wald Test	No. Inst	No. Obs	No. Groups
Model 1	0,0002	0,0756	0,8016	0,0000	30	468	156
Model 2	0,9154	0,4210	0,6863	0,0002			
Model 3	0,0953	0,7623	0,2669	0,0000			
Model 4	0,0000	0,0581	0,8940	0,0000			
Model 5	0,8555	0,3590	0,6003	0,0001			
Model 6	0,9975	0,0518	0,0511	0,0025			

Source: own calculations

4.8 Robustness check

Table 32 illustrates the R^2 and adjusted R^2 ordinary least square (OLS) results. Nadeem et al. (2017) posits that a three to four-fold change in the R^2 between the static and dynamic OLS regression and the statistical significance of the lagged regressor in a dynamic OLS model indicates the presence of a dynamic relationship. We observe that the lagged regressor is significant at the 0.1% level and on average a two-fold change in the R^2. Whilst the magnitude of this change is not entirely in line with Nadeem et al. (2017), we can conclude that a dynamic relationship exists between the dependent variable and its lagged regressor, which supports the use of the DGMM.

Table 32. Robustness Check: Static and Dynamic OLS

Brazil	**Static OLS**		**Dynamic OLS**			
Model	**R^2**	**Adj R^2**	**R^2**	**Adj R^2**	**ΔR^2**	**Δ Adj R^2**
1	0,3524	0,3403	0,5710	0,5610	1,62	1,65
2	0,4445	0,4342	0,8926	0,8901	2,01	2,05
3	0,4466	0,4363	0,7116	0,7049	1,59	1,62
4	0,2712	0,2591	0,5406	0,5310	1,99	2,05
5	0,3492	0,3384	0,8855	0,8831	2,54	2,61
6	0,3773	0,3669	0,6923	0,6858	1,83	1,87
Indonesia	**Static OLS**		**Dynamic OLS**			
Model	**R^2**	**Adj R^2**	**R^2**	**Adj R^2**	ΔR^2	**Δ Adj R^2**
1	0,5048	0,5003	0,6485	0,6445	1,28	1,29
2	0,4840	0,4793	0,9124	0,9114	1,89	1,90
3	0,2316	0,2247	0,6509	0,6470	2,81	2,88
4	0,3928	0,3878	0,6122	0,6082	1,56	1,57
5	0,4108	0,4060	0,9096	0,9087	2,21	2,24
6	0,2033	0,1969	0,6471	0,6435	3,18	3,27
South Africa	**Static OLS**		**Dynamic OLS**			
Model	**R^2**	**Adj R^2**	**R^2**	**Adj R^2**	ΔR^2	**Δ Adj R^2**
1	0,3806	0,3660	0,5074	0,4927	1,33	1,35
2	0,5766	0,5666	0,9400	0,9382	1,63	1,66
3	0,5436	0,5328	0,8345	0,8295	1,54	1,56
4	0,2959	0,2812	0,4689	0,4549	1,58	1,62
5	0,4853	0,4745	0,9387	0,9371	1,93	1,97
6	0,3644	0,3511	0,8249	0,8202	2,26	2,34

****Note: the p-value of the lagged regressor for all models significant as the 0,1% level.**

Source: own calculations

4.9 Discussion and Summary

We infer that across the three countries, investors still reward investment in physical capital as an important driver of firm valuation given the positive association between MB and CEE. Furthermore, firm valuation in South Africa has a negative association with HCE and SCE which implies a misalignment between the employees' skills and knowledge as well as market perceptions of future returns expected from investment in technology, systems and processes. In South Africa there is no association between physical, human capital and profitability which contradicts the findings of Brazil and Indonesia. The results suggest that firms in South Africa would rather invest in innovation such as patents, trademarks, systems and processes to yield positive returns notwithstanding the fact that it might hinder shareholder value creation.

Congruent with its status as an innovation overperformer (World Intellectual Property Organisation, 2023), we note the positive association between human capital efficiency and profitability in Brazil and Indonesia. It suggests that firms regard investment in human capital as a positive driver of performance; however, South African firms appear to be inefficient in respect of human capital investment given the lack of statistical significance in relation to profitability. Considering the country's challenges to attract and retain highly-skill employees in the knowledge sector (Yu, 2022), this result underscores the bias towards physical capital investment.

However, we also observed that the composite measurement, VAIC™, is positively associated with profitability across all countries, suggesting that firms leverage both intangible and tangible capital to drive returns. In other words, firms recognize the value of investing in both intellectual capital (IC) and physical assets to generate profit. However, the signal from investors from a valuation perspective appears contradictory. The relationship between VAIC™ and market-to-book value (MB) in South Africa and Indonesia is not significant, implying that the market attribute more value to investments in tangible capital over intangible assets. Therefore, investors may penalise firms that prioritise the latter. This assertion is consistent with the results for the individual IC components and MB, but contrasts with findings from Brazil, where investors reward firms that invest in both IC and physical capital at an aggregate level.

We conclude that the result of the study across the three countries are mixed. The conclusion is similar to other academics. Investors in South Africa and Indonesia reward firms from a valuation perspective that invest in physical capital; whereas, in Brazil investors reward investment on both physical and intangible capital. However, firms in the study appear to favour investment in both intangible and tangible capital to drive performance. This is positive given the transition to a knowledge economy.

In this chapter we conducted various diagnostic tests and modelled the DGMM regressions. While the diagnostic tests appear to be correctly specified for instrument validity, two models showed AR (2) autocorrelation which could be the result of inaccurate data, omitted variables amongst others. Notwithstanding, given the robustness check, we can conclude that a dynamic relationship does exist between the dependent variables and its lagged regressor. Additionally, we analysed and discussed the results of the various DGMM models of the countries that demonstrates mixed results from an investor and firm perspective.

In chapter 5 we will provide concluding remarks of this study, detail the limitations of the study and offer suggestions for future research.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

The aim of this research was to build on prior knowledge of Chen et al. (2005), Nimtrakoon (2015), Nadeem et al. (2017) and investigate the relationship between VAIC™, its components, firm performance and firm value for emerging markets namely, Brazil, Indonesia and South Africa. Our objective was:

- To determine the relationship between VAIC™ and firm performance
- To determine the relationship between VAIC™ and firm market value
- To determine the relationship between the components of IC and firm performance
- To determine the relationship between the components of IC and firm market value
- In each of the instances above, to compare the outcome for South African firms with that of the other countries included in the study.

In this study, we hypothesised the direction of the relationship between the dependent and explanatory variables. We further examined the literature that underpins the existing research, which includes the definitions of IC and its various components. Moreover, we reviewed the application of the VAIC™ model from a developed, emerging, cross-country perspective and the impact of lags on firm performance. We reviewed and outlined the applicable regression models including the associated diagnostic tests.

Generally, the results were mixed across the three countries and consistent with the findings of Chen et al. (2005), Nadeem et al. (2017), Nadeem et al. (2018) in Brazil for model 1 and 4, however for models 3 and 6 the results contradict Nimtrakoon (2015), Nadeem et al. (2017) as well as Bhattu-Babajee and Seetanah (2022). In Indonesia, support was found for models 1 and 4 by Maji and Goswami (2016), Nimtrakoon (2015), Nadeem et al. (2017), Chen et al. (2005) including Soetanto and Liem (2019) but contradicted by Firer and Mitchell Williams (2003), Bhattu-Babajee and Seetanah (2022) as well as Olarewaju and Msomi (2021). Firer and Mitchell Williams (2003) including Firer and Stainbank (2003) support our findings in the South African market, but it is contradicted by Nadeem et al. (2017). Moreover, we inferred that investors in South Africa and Brazil, rewarded firms who invested physical capital compared to firms in Brazil that invested in both IC and physical capital to enhance firm value, given the overall significance and direction of the variables. However, firms appear to prefer to invest in both intangible and physical capital to generate shareholder returns from a performance and productivity perspective which bodes well for the transition into a knowledge-led economy.

5.1 Limitations of the study

The VAIC™ model does not account for relational capital or innovation capital, proxied by R&D costs akin to Nadeem et al. (2019), due to a lack of data availability. Given the approach to a balanced panel data set and exclusion of enterprises that did not report salaries and wages, the study is exposed to survivorship bias, which could subject the models to incorrect inferences due to omitted variables and data quality. Furthermore, during the period under consideration, the novel COVID-19 virus broke out worldwide and adversely impacted firms' trading. The study did not account for this particular crises, akin to Nadeem, et al. (2017) who accounted for the global financial crises (GFC) in their study, and therefore could be regarded as a material limitation.

5.2 Recommendation for future research

Consequently, future research could be extended to account for the impact of COVID-19 and include research and development as a proxy for innovation capital subject to data availability. Moreover, research can include a wider cross-country analysis and compare the GFC (2006 – 2010) and COVID-19 events (2019 -2023) to assess to what extent the crises hindered or accelerated IC investment.

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