Intellectual Capital and Firm Performance: Evidence from Developed, Emerging and Frontier Markets of the World

A thesis
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I dedicate this work to my beloved wife Kiran Nadeem, my new born Hassan Nadeem, my parents, my sisters and my brother for all their love, support and encouragment.

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Over the past decade, intellectual capital and firm performance (IC-FP) has become an emerging strand of accounting and finance. The evolution of various theories such as Resource-Based View (RBV), Resource-Dependency (RD) and Learning-Organisation (LO) has further amplified the importance of intangibles for firms as well as for economies. RBV argues that a firm should build its competitive advantage based on the unique values, knowledge and skills of the employees and production processes of the firm. These unique attributes have been combined in the literature under one term "Intellectual Capital" (IC). The transformation from physical resource-based to knowledge-based economies has led policy-makers to rethink their investment levels in intellectual resources. The past decade has witnessed an increasing number of studies linking IC efficiency with firm performance. These studies, however, have reported divergent results, which not only make IC disclosure limited but also left the managers indecisive about their investments in IC. The literature attributes these divergent results to a number of factors such as small samples in the studies, short time period, IC measurement models and/or economic development level of the economy under study. Moreover, the IC-FP relationship has always been considered static hence the literature ignores the potential endogeneity existence.

This study is the first attempt to investigate the IC-FP relationship in developed, emerging and frontier markets using over 7,100 listed firms for the period 2005-2014. We apply the system generalized method of moments (SGMM) to overcome the problem of endogeneity and so produce unbiased results. The findings reveal that IC efficiency is highest for developed markets followed by emerging and lowest for frontier markets. Empirical evidence suggests a significant positive relationship between IC and FP in almost all types of market. The significant positive relationship between human capital (HC) and FP in static models disappears when SGMM is applied. This study makes some important adjustments in the value added intellectual coefficient (VAIC) model and presents A-VAIC model to overcome criticism of the original VAIC model. We then test A-VAIC on developed and emerging markets and report more consistent results where HC is also significant and positive with FP in almost all markets. Furthermore, the results reveal that IC efficiency remained unchanged during the 2008 financial crisis. The final results, though endorsing RB, RD and LO theories, posit that IC increases FP in all types of economy (developed, emerging and frontier) and that investment in IC should be on-going process.

Keywords: Intellectual capital, endogeneity, GMM, A-VAIC, developed emerging and frontier markets

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Chapter 1

Introduction

1.1 Introduction

Intellectual capital (IC from here on) has long been ignored as a vital contributor in the financial performance of a firm. This ignoring is because conventional accounting standards such as *Financial Reporting Standards* (FRS 138), restrict the disclosure of intangible assets (except goodwill) on firms' balance sheets (Wang & Chang, 2005; Shiu, 2006; Gigante, 2013; Joshi *et al.*, 2013). It is only recently that researchers have started to explore this topic and realized that IC is not only the driver of a firm's progress but also enables a firm to build its competitive advantage. Different researchers (Edvinsson & Malone, 1997; Firer & Williams, 2003; Ederer, 2006) define IC differently. IC generally is the intangible assets that play an important role in the wealth creation process of a firm but are not recorded on the firm's balance sheet like physical assets (Burgman *et al.*, 2005). IC in other words is the totality of all those skills and competencies possessed by the employees that create wealth for the firm (Huang, 2007). O'Donnell *et al.* (2003) and Demediuk (2002) argue that knowledge and skills have started replacing physical assets in knowledge-based modern economies. In this regard, Ederer (2006) suggests that nothing will be more trouble to the future of Europe than the ability of countries' governments, employees and firms to modernize a system that depends on the efficiency of decision making and the quality of human capital.

According to Cañibano *et al.* (2000), the majority of manufacturing economies are being replaced by *"knowledge driven, fast changing and technologically intensive economies",* where IC has become the major driver of value creation for firms (H.-Y. Su, 2014). Different measures have been adopted in some developed countries to transform their input based economies to knowledge-based economies, e.g., New Zealand (New Zealand Ministry of Economic Development, 1999), England (United Kingdom Trade and Industry Ministry, 1998) and Scotland (Scottish Office, 1999). These measures were adopted in anticipation of the shift from physical input based development to knowledge-based development. The World Bank Report (1998) highlights the importance of knowledge-based inputs in developed countries where the equilibrium between knowledge-based and resourced based output has moved towards the former because it has become the most important driver of the living standards of the citizens (Dahlman, 1998).

1.2 Resource Based View & Knowledge Economy

Resource Based View (RBV) first identified the link between a firm's internal activities such as managerial decisions and external environment such as what customers actually demand from the firm. The internal activities refer to the firm's capacity to utilize its available resources in accordance with the external demands (Amit & Schoemaker, 1993). The RBV of a firm, introduced by Barney (1991), believes that a firm's competitive advantage should consist of inimitable values, rare capabilities[1] and actions. The author divided these rare values and inimitable actions into both tangible and intangible assets for the firm. Intangible assets comprise skills, knowledge and processes that can be combined under the term *"Intellectual Capital"*. These values, based upon knowledge and skills, are measured in terms of the client's perception rather than quantitative tangibility, which means quantity is replaced with values (Barney, 1991). In the industrial age, the only measure of wealth creation was net increase in the quantity of production but in today's knowledge economy the trend includes the accumulation of knowledge, skills, creativity and processes termed as IC.

According to the OECD (1996) report, when the use of knowledge, skills, production and distribution becomes the major driver of a firm's growth and its profitability across the market, the economy can be classified as a knowledge-based economy. This can describe an economy where the knowledge and skills of the humans play an important role in wealth creations. Lev (2000) defines the knowledge economy where human inputs replace older production based and mercantile economic activities, not only at the company level but also in national growth. This shift from production based economies to knowledge-based economies has generated a significant growth in measurement and management of IC both nationally and globally (Cabrita & Vaz, 2005). Cahill and Myers (2000) argue that the effective measurement and management of IC is the result of the shift towards knowledge-based economies. Moreover, dependence of firms on effective measurement and management of IC increases with the increased dominance of knowledge-based economy (Sveiby, 1997; Cabrita & Vaz, 2005; T. A. Stewart, 2007). In this regard, firms today make significant investment in training and educating staff in order to develop huge resources of IC, which is essential in a knowledge-based economy (Foray, 2006).

1.3 Background to the Study and the Research Problem Statement

Existing studies that attempt to explain the relationship between IC and firm performance have produced mixed results. For example, a number of studies (Chen *et al.*, 2005; Tan *et al.*, 2007; Clarke *et al.*, 2011) find a significant positive relationship between IC and firm performance whereas other studies (Firer & Williams, 2003; Ho & Williams, 2003; Chan, 2009b) find no significant relationship. These mixed results are attributed to either the methodology used (such as using the VAIC model) to

[1] Unique processes and procedures by which a firm converts its input into output.

measure IC or the stage of economic development of the country being studied, *i.e.,* developed or developing. Apart from other limitations of previous studies such as small datasets, limited scope. In our opinion, there is another missing link in the literature in that existing studies have considered this relationship in only one direction, *i.e.*, IC efficiency affects the financial performance of the firm. Therefore the missing link in the literature is an investigation of whether firms' past performance affects the future IC efficiency (the presence of *endogeneity*). Most studies on IC (Sveiby, 1997; Pulic, 1998; Bontis, 2001; Pulic, 2004; Subramaniam & Youndt, 2005) agree at least on three components of IC namely human capital, structural capital and relational capital. Each of these components requires appropriate investment to accumulate IC resources (Rastogi, 2003). Firms' investment in these resources are objective driven, *i.e.*, these investments are made to achieve specific goals. For example, firms invest in human capital to increase their motivation level or to enable employees to generate new ideas. Similarly, investment in R&D (also known as *structural capital*) are made to bring innovation into existing products or to bring new products to the market. Considering that investment in IC resources is objective-driven, the investment source needs to be discussed. According to the *Pecking Order Theory* of capital structure (Myers & Majluf, 1984), firms follow a particular order while generating their funds. They argue that firms utilize internally generated funds as the first priority and then think about loans or raising equity. The main source of internally generated funds is firms' profits.

The above argument postulates that a firm's investments depend on its profit level if they follow pecking order theory. Moreover, it is quite practical and normal that firms will make more investments (in the form of salary increments or bonuses) in their employees when profits escalate. Similarly, for R&D firms tend to make more investments when they observe higher profits or growing cash flow (Chauvin & Hirschey, 1993; Mulkay *et al.*, 2001; Becker, 2013). In this regard, Brown *et al.* (2009) in their study about R&D expenditure in mature high-tech firms in the US, find that cash flow correlates positively and significantly with the level of investment in R&D. Harmantzis and Tanguturi (2005) in their study on the determinants of R&D expenditure in US telecommunication firms, find that firms' last year performance, in terms of market value and revenue, significantly affects current year investment in R&D. This evidence suggests that the relationship between IC components and firm performance is not unidirectional but bidirectional, which means that lagged firm performance affects current or future year IC efficiency. This argument is also consistent with Murthy and Mouritsen (2011)'s study that firms' financial performance is a basis for determining investment in IC.

If the above discussion is true, *i.e.*, the relationship between IC and firm performance is two-way[2] then, according to Baltagi (2008) and Gujarati (2012), this is a dynamic relationship and the application of static estimators such as OLS and fixed-effects (FE) will lead to biased results – which is what has been done in the literature. Departing from previous studies, this study focuses on this important methodological aspect and analyses step by step if this relationship is really dynamic in nature. We apply series of tests such as dynamic OLS and the Wooldridge (2002) test of strict exogeneity to investigate the presence of endogeneity. Then we apply a *dynamic panel data* (DPD) estimation to investigate the true relationship between IC and firm performance after catering for econometric problems such as *heteroscedasticity, autocorrelation* and *endogeneity*.

Firer and Williams (2003) argue that the concept of IC in emerging and developing countries is still in its initial development stages. Because of increasing global dependence on emerging economies, there is a strong need to emphasize the development of IC in different socio-economic environments. Boekestein (2009) argues that due to a scarcity of physical resources, firms should make better use of their non-physical assets such as IC to create value for stakeholders. Being the key source of competitive advantage and the point of focus by the businesses and government organizations, IC is still not widely explored especially in emerging and under-developed countries (Pedrini, 2007). Therefore, this study aims to investigate the efficiency of IC and its impact on firms' financial performance in developed, emerging and frontier countries[3] to provide consistent results from large datasets.

A number of studies such as Vishnu and Kumar Gupta (2014), Gan and Saleh (2008) and Firer and Williams (2003), argue that most studies on IC are limited to either a small sample of a specific industry or small sample period. Therefore, this study includes all listed firms in developed, emerging and frontier countries for a period of 10 years (2005-2014) and avoids such limitations. A comparison across different economies enables this study to identify the differences in the efficiency of IC in developed, emerging and frontier countries. Ståhle and Bounfour (2008) argue that IC can be used as a pillar for economic growth especially in developing countries during financial turmoil. The studies exploring the efficiency of IC during financial crisis are still scarce in the literature[4]. The current study aims to explore the relationship between IC and firm performance during the 2008 financial crisis to understand how companies survive and maintain their growth during financial crises.

The increasing importance of IC has motivated researchers to develop different ways to measure and manage the efficiency of IC (Serena Chiucchi, 2013) but however, having an IC measurement model

[2] This phenomenon is also known as the case of endogeneity (mainly because of simultaneity).

[3] Frontier countries as defined in MSCI index as those markets where (a) institutional framework stability is at modest level, (b) operational framework efficiency is at modest level, and (c) where inflow/outflow of capital is only partial.

[4] Apart from couple of studies such as, Young *et al.* (2009) and Sumedrea (2013)

free from criticism is still a dream. This study applies one of the most widely used monetary-based IC measurement model (VAIC) of Pulic (1998). This model has been criticised by authors (Ståhle *et al.*, 2011) especially for its measure of structural capital. Therefore, with the support of appropriate literature[5], our study uses R&D expenses as a proxy for innovation capital, which replaces structural capital in the VAIC model[6]. This study also makes some other important changes in the VAIC model and introduces an adjusted-VAIC model to increase the reliability of the IC measurement model.

1.4 Significance of the Study

Existing studies on IC and firm performance have often ignored an important econometric aspect, *i.e.,* the presence of endogeneity (mainly because of *simultaneity* and *un-observed heterogeneity*). This study applies a series of tests such as dynamic OLS and Wooldridge strict exogeneity test to check for the endogeneity in the IC - firm performance relationship. This study then applies a dynamic panel data estimation to produce consistent, unbiased results. For comparison purposes this study also applies OLS and fixed-effects estimators.

The scope of most previous studies has been limited to either one country or industry (Firer & Williams, 2003; Pek, 2005; Vishnu & Kumar Gupta, 2014). According to these authors, the generalization of the results from previous studies is difficult because of small data samples. Therefore, this study extends the scope to three different economic environments, *i.e.,* developed, emerging and frontier markets. This will not only enable generalization of the results but also increase our understanding about the efficiency of IC in different regions of the world. The study also investigates the relationship during 2008 global financial crisis to check for the role of IC during financially turbulent periods.

This study replaces the structural capital measure of the VAIC model with innovation capital (INVCE) and changes its proxy measure. This study also makes some other important adjustments in the VAIC model to overcome general criticism of the original VAIC model. The adjusted VAIC model is then applied to developing and emerging markets to check for the usefulness of the adjustments in the VAIC model. These unique features depict the overall significance of this study.

1.5 Research Questions

Our study aims to answer the following questions:

1. What is the efficiency of IC in developed, emerging and frontier markets?
2. Is the relationship between IC and firm performance dynamic?

[5] Which is further discussed in our chapter 6.
[6] This new proxy will be tested in developed and emerging countries because of data availability.

3. What is the impact of IC on firms' financial performance in developed, emerging and frontier markets?
4. What is the role of IC in the financial performance of firms pre, during and post the 2008 global financial crisis in developed, emerging and frontier markets?
5. Does innovation capital increase the explanatory power of the VAIC model?

1.6 Research Objectives

The research objectives are:

- To analyse the dynamic nature of the relationship between IC and performance.
- To investigate whether the efficiency of IC differs in three different economies: developed, emerging and frontier economies.
- To test whether the impact of IC on a firm's financial performance differs in three different economies: developed, emerging and frontier economies.
- To determine the role of IC in value creation process during the 2008 global financial crisis.
- To examine whether the inclusion of INVC increases the explanatory power of the VAIC model.

1.7 Definition of Intellectual Capital

No universally accepted definition of IC exists despite its importance to the firms (Cañibano *et al.*, 2000). According to Edvinsson and Malone (1997), IC consists of all entities such as knowledge, technology, a firm's relationships with its customers and the professional skills of the firm's employees. Dividing IC in to three components, *i.e*., human capital, structural capital and physical and/or financial capital. Vergauwen *et al.* (2007) define human capital as skills, knowledge and professionalism owned by the personnel. Structural capital, however, consists of the working environment, and research and development in the organisation (Guthrie *et al.*, 2012). Bontis (2001) further divides structural capital into two types: (a) structural capital that is composed of strategic plans, patents and copyrights owned by the organisation; and (b) relational capital in the form of relationships with customers and suppliers. A summary of IC definitions is presented in Table 1.1.

Table 1.1 Summary of the Different Definitions of IC

Author(s)	Definition
Edvinsson and Malone (1997)	IC can be recognized as knowledge which can be converted into value.
Bassi (1997)	IC consists of all types of knowledge and its components include human capital, structural capital and customer capital.
Stewart and Ruckdeschel (1998)	IC is the sum of knowledge, intellectual property, skills and material which can be used to create wealth for an organization.
Roos *et al.* (1997)	IC consists of those assets which are not fully recorded on the balance sheet of a firm including what is in the head of employees and what is retained by the company when the employees leave.
Edvinsson and Malone (1997)	IC is the sum of skills, experience, knowledge, technology, relationships with customers which contribute towards the competitive advantage of Skandia in the market.
Brooking (1996)	IC is the difference between the book value and the amount someone is willing to pay for the company.
Booth (1998)	IC is the ability of the firm to convert new ideas into a product.
Sveiby (1997)	Sum of internal structure such as processes and external structure.
Bontis (1999)	IC is the sum of human capital, structural capital and relational capital.
Guthrie and Petty (2000)	The value of intellectual assets belong to both company and employees.
Harrison and Sullivan Sr (2000)	Knowledge which contributes towards profit of the organization.
Brennan and Connell (2000)	IC is the equity of the firm based upon knowledge.
Ordóñez de Pablos (2003)	IC is the sum of knowledge-based resources which give a firm a competitive edge in the market.
Subramaniam and Youndt (2005)	Knowledge resources used for competitive advantage.
Nikolaj *et al.* (2005)	IC can be thought of a mobilizer of employees, assets, technology which keep various assets together in the value creation process.
Zerenler *et al.* (2008)	IC is the sum of human capital, structural capital and relational capital which belongs to both employees and organization.
Choong (2008)	IC is the representative of all the expenses on R&D, training, operations, employees, brand, patents, trademarks, processes, and licences.

*Originally sourced from Hsu and Wang (2012) and then modified

In light of the above definitions by different authors, we define IC as the sum of unique intangible assets including the knowledge and skills of the employees, inimitable processes and the relationships with customers, which contribute significantly towards the wealth of the firm.

1.8 Components of Intellectual Capital

Like the various definitions of IC, the literature divides IC into several components.

1.8.1 Human Capital

Human capital (HC) consists of skills and knowledge possessed by employees and goes with them when they leave the firm (Čater & Čater, 2009); such intangible capital cannot be retained by the firm. In context of the RBV, Wright *et al.* (1994) argue that a firm can gain a competitive advantage through a pool of human capital and, moreover, firms today evaluate their available resources to select a suitable strategy. According to Subramaniam and Youndt (2005), human capital is the key resource of the firm in an era where knowledge and skills of the employees are essential to create a sustainable competitive advantage. HC theory further explains the importance of HC as a major driver of a firm's productivity and assesses the employees' possession of necessary skills and knowledge to fulfil the requirements of their jobs. HC is important in industries such as banking and pharmaceuticals where firms compete in innovation and advancement. These firms need employees who possess innovation and problem solving skills.

Hsu and Wang (2012) argue that a firm can improve its performance so long as its employees continue to improve their knowledge and skills because HC focuses on the value addition to the business in terms of profitability. HC contributes towards organizational efficiency in many ways such as decision making, which improves when employees possess the required skills. In this way, a firm can better fulfil the demands of customers when employees possess such innovative skills (Luthans & Youssef, 2004). Roos *et al.* (1997) divide HC into two types of skills and knowledge. The first set of skills solely belongs to employees and cannot be retained by the firm such as loyalty, employee professionalism, personal attributes and experience. The second set of skills can be shared between employees such as creativity, team work, affirmative working environment and know-how. In light of the literature, we define human capital in this study as the "*sum of knowledge, skills, creativity and personal values of the employees which (a) contribute towards both the tangible and intangible assets of the firm and (b) can be further improved by training and other similar seminars".*

1.8.2 Structural Capital

Structural capital (SC) is a component of IC that remains with the firm when employees leave it. SC consists of policies, procedures, systems, databases and other infrastructure facilities that enable human capital to work properly. According to Hobley and Kerrin (2004), SC consists of the procedures, processes and systems in which employees actually make use of their available knowledge and skills towards wealth creation. The authors discuss the processes (how a firm converts its input into final product) as a unique resource of the firm which, once acquired, then later it can be retained and legally protected by the firm. Firms with sound SC will give their employees opportunities to exploit their knowledge and skills to create competitive advantage (Florin *et al.*, 2002). Conversely, a firm with poor SC fails to achieve its performance targets (Widener, 2006). In today's knowledge-based economies, firms are struggling to differentiate on the basis of quality and innovation. Thus it is necessary to invest in SC, which allows HC to fully utilise the skills and creativity, which increases the firm's performance. we define structural capital as the "*sum of unique processes which firms acquire through R&D and then protect in the form of patents and copyrights"*.

1.8.3 Customer Capital

Customer capital (sometimes referred to as relational capital) is defined in the literature as the relationships of the firm with its stakeholders such as customers, suppliers, partners, investors, distributers, etc. (Roos *et al.*, 1997; Cabrita & Vaz, 2005; Hormiga *et al.*, 2011). Customer capital *(CC)* is considered a component of IC that strengthens the external links of the firm; advertising, selling and marketing investments are major sources of building this capital. CC is also defined as the sum of actions within communities concerned with the deployment of resources with the help of social structure (Cañibano *et al.*, 2000; Bontis, 2001; Hsu & Wang, 2012). In other words, CC can be described as the sum of the firm's implicit resources created and implemented by interacting with individuals and other firms.

Firms with strong CC can establish more relationships with partners, which increases their interdependencies. Social exchanges resulting from interdependencies increase trust, which sometimes replaces explicit contracts (Dyer & Singh, 1998). Through these exchanges, employees learn new values and skills that will directly contribute towards wealth creation for the firm. In light of the literature, we define CC as "*the sum of shared values, strategic alliances and relationships with all stakeholders which results in an influx of knowledge that helps better understand the external demands",* whereby the company's wealth is maximized.

1.8.4 Innovation Capital

Innovation capital (INVC) refers to the ability of the company to innovate in terms of new products, technology and distributive channels. R&D is the major investment that results in innovation capital, which plays a vital role in enhancing proximity to suppliers (Romijn & Albaladejo, 2002) argue that a company should make sufficient investment in R&D to accumulate innovation capital. Note that the literature sometimes use innovations capital and structural capital terms interchangeably.

1.8.5 Social Capital

Nahapiet and Ghoshal (1997) argue that *social capital (SsC)* consists of resources acquired by the firm through relationships between individuals or with society. SsC results from human connections based on confidence and socialisation that contributes towards competitive advantage for the firm and the welfare of society (Cohen & Levinthal, 1990; Nahapiet & Ghoshal, 1998). Bueno *et al.* (2004) conclude that SsC plays a vital role in the overall development of IC.

1.9 Importance of Intellectual Capital for Firm Performance

In the 1950s, a Kiwi's average income was among the highest in the world (Derby, 2012) but by 2006 New Zealand was at the bottom of developed countries in the same list. A major reason given by Derby was that New Zealand is remote and geographically isolated – thus it is difficult to export high volume goods. This disadvantage, however, can be overcome by expanding knowledge-based industries, by exporting and selling ideas, patents and copyrights. The author recommends New Zealand exploit the skills and talent of its people to create added value in service export oriented industries and turn the country's economy into a resource based economy – "an economy where intellectual capital is the major driver of value creation for the firms".

Hsu and Wang (2012) argue that the interaction between external environment and a firm is related to the firm's performance and the pursuit of best performance of the managers who develop strategies to meet the external environment. Hence, the strategies should be based upon inimitable knowledge-based resources. IC is the aggregate of all knowledge-based resources that contribute toward the competitive advantage and replace most of the physical capital based resources such as machinery and plant (Boulton *et al.*, 2000). IC becomes more important for service industries such as insurance, banking and telecom, because these industries rely more on the knowledge and skill of the employees for value creation, which increases the need for the measurement and effective management of IC (Boulton *et al.*, 2000). The measurement of IC is important because it is the main driver of value creation in knowledge-based economies (Rangone, 1997) but, unfortunately, the current industrial based accounting measures are poorly adapted to service these realities (Bandt, 1999).

The huge difference between market value and book value of the firm is attributed to the existence of IC (Brennan & Connell, 2000) . Financial estimates show that the M/B[7] ratio of S&P[8] companies was six in 2010 compared with about one in the 1980s (see Figure 1.1); this reflects the existence of IC (Lev, 2000).

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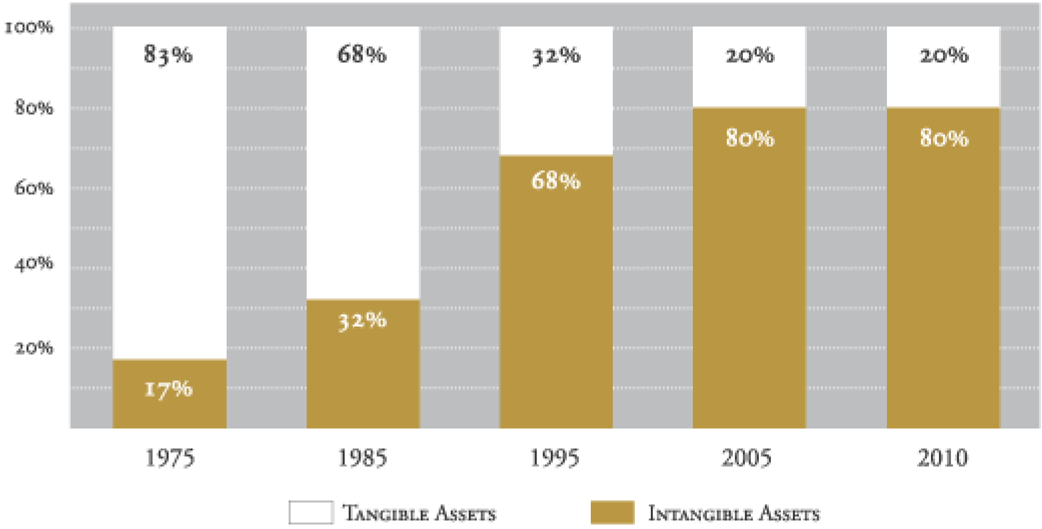
[7] Market to book value of the firm
[8] Standard and Poor's 500

Figure 1.1 Tangible and Intangible Asset Distribution of S&P 500 Companies between 1975 and 2010.



Source: Tomo (2010)

To explore the existence of IC and its relationship with a firm's financial performance, many research studies have been carried out over the past decade. Pek (2005) analysed the performance of IC in Malaysian banks using 2001-2003 data and found that the efficiency of HC element of IC is relatively higher than the other two elements of IC namely SC and capital employed. Pek (2005) finds that most domestic banks in Malaysia failed to show any improvement in terms of IC efficiency over the study period. Foreign banks, however, exhibited higher efficiency scores than domestic banks. The study concludes that investing in IC generates more return than investment in physical assets.

To try to study the efficiency of IC and its impact on a firm's financial performance in a developed country, Clarke *et al.* (2011) measured the VAIC of publically listed companies in Australia from 2004-2008 and found a positive relationship between VAIC and the performance of firms. The study also showed that current investment in the different components of IC may yield returns in future periods. The authors analysed the impact of a lag year investment in IC on the current year financial performance of the firm and reported a positive relationship. The study also measured the mediating role of IC on the relationship between capital employed and the financial performance of the firm. Clarke *et al.* (2011) argue that IC cannot work alone, rather it has to be accompanied by some other forces such as financial capital. Nonetheless, the authors conclude that if proper investment in IC is made in any given year, it can contribute significantly to the firm's financial performance in the same year as well as in future years.

Pulic (1998) is the founder of *value added intellectual coefficient* (VAIC) that measures the efficiency of the three components of IC, namely, human capital, structural capital and financial capital[9]. The author suggests that when the value of VAIC increases it implies that IC is being efficiently managed for value creation. Pulic (2004) used data from 1992 to 1998 for 30 randomly selected publicly listed companies from the FTSE 250 and reveals a strong relationship between IC and the market value of the firm.

Chen *et al.* (2005) used data from all the publicly listed companies on the Taiwanese stock market and analysed the efficiency of IC and its impact on firms' financial performance. The authors used VAIC first as an aggregate measure of efficiency and then its components, *i.e.,* human capital, physical and financial capital and structural capital, as individual efficiency measures. ROA, ROE, employee productivity and market-to-book value were used as financial performance indicators. The authors used R&D and advertising expenses as mediators because they believe that these expenses play a significant role in value creation and innovation processes. Using data from 1992 to 2002, the authors find that the M/B value of the firm is significantly correlated with VAIC, physical capital and human capital but no correlation with structural capital. Chen *et al.* (2005) also report that R&D expenses significantly correlate with M/B value suggesting that these expenses play a vital role in value creation. Using lagged independent variables of three years, they analysed the relationship between VAIC and its components and the firms' financial performance and conclude that financial capital is significantly related with firms' future performance. This implies that one could forecast the firms' future performance from lagged investment in IC.

Nevertheless almost all the aforementioned studies highlight the importance of IC for firms in the knowledge economy era. Although the literature documents mixed results so far, it provides a clear indication that much research is still required in this area to further explore the role of IC for firms. Further research is also required to study the elements of IC such as innovation capital, which are ignored in the literature. With decreasing natural resources and increasing raw material prices, firms need to produce new efficient ways of production. This indicates that the importance of IC will further increase in future with increasing competition.

1.10 Intellectual Capital during Financial Crises

The 2008 global financial crisis was the biggest event of the first decade of the twenty first century. It was apparently caused by poor surveillance systems and management flaws in strategic decision making in financial markets (Lin *et al.*, 2012). Lin *et al.* (2012) find a positive correlation between National Intellectual Capital (NIC) and GDP per capita while studying NIC for over 48 countries from

[9] More about the structure and derivation of VAIC will be discussed in methodology chapter.

2005 to 2010. Globalization and turbulent effects plus a complex business environment have forced many firms to look for new ways to use all available resources at maximum possible efficiency. According to Sumedrea (2013), the 2008 global financial crisis and its after effects have forced firms' management, practitioners and scholars to analyse the relationships between firms' financial performance and available resources. According to the author, the importance of IC becomes more crucial in financial turbulence where firms look for new skills and solutions to move away from the financial crisis. Sumedrea (2013) concludes that during financial crises the survival of firms can be linked to IC in terms of the company development. More specifically, human skills, knowledge and creativity are the factors that contribute to firm performance in financially turbulent times. Nevertheless both the aforementioned studies agree that there is need for more research to explore the role of IC during a financial crisis when firms face scarcity of physical resources.

1.11 Structure of the Thesis

The rest of the thesis is organised as follows: Chapter 2 reviews the relevant literature including the evolutionary stages of IC, models to measure the efficiency of IC, previous studies on IC and firms' performance and the theoretical framework of the research. Chapter 3 explains the methodology and data used in this study. Chapter 4 presents and discusses the descriptive and empirical results from static estimators (OLS and fixed-effects). Chapter 5 presents and discusses the empirical results from dynamic panel data estimation. Chapter 6 discusses the shortcomings of the VAIC model, makes some adjustments, presents an adjusted VAIC model and applies this adjusted model to measure IC efficiency. Finally chapter 7 discusses the major findings of this study, policy implications and outlines directions for future research.

Chapter 2

Literature Review

2.1 Introduction

The world's economy has significantly moved from an industrial era to a knowledge one over the last approximately three decades. In a knowledge driven economy, the traditional factors of production such as land, buildings and machinery are being replaced with knowledge-based resources such as employees' knowledge and skills (Stewart & Ruckdeschel, 1998). The RBV of the firm also focuses on the long-term competitive advantage of the firm by maintaining its strategic resources such as knowledge and skills, which in turn can yield above average profits for the firm (Peteraf, 1993). These knowledge-based resources, which create value for the firm, are commonly termed Intellectual Capital (Stewart & Ruckdeschel, 1998). According to Barney (1991), a firm should develop inimitable, valuable and rare resources to build a sustainable competitive advantage, which defines a firm's profitability (Amit & Schoemaker, 1993). Knowledge is a vital resource of a firm that can be developed, transferred and used for competitive advantage within and across industries (Nonaka, 1991; Grant, 1996).

With this shift from physical assets based economy to a knowledge-based economy, IC (commonly known as the difference between market value and book value of the firm) has become the key to the value creation process of a firm (Edvinsson & Malone, 1997; Petty & Guthrie, 2000). This new trend makes the measurement and management of IC an important topic in today's knowledge-based economies (Brooking, 1996; Roos *et al.*, 1997; Bontis, 1999). Knight (1999) argues that a business must invest in its personnel for the better management of IC, which will in turn build competitive organizational and relational capital. Thus spending on IC is no longer being treated as cost rather it is recorded as an investment (Guthrie, 2001).

2.2 Development Phases of Intellectual Capital

This section discusses the evolutionary stages of IC and how IC emerged as vital contributor towards value creation in a firm.

2.2.1 Evolution of Intangible Resources

In the past, the role of intangible assets in value creation has been ignored because of the dominance of physical assets on firms' balance sheets (Jhunjhunwala, 2009) hence, firms always try to dress up physical assets because they influence the net worth of the firm. Today, however, the success of firms mostly depends upon the effective use of their intangible assets including employees' knowledge, skills and other invisible resources such as patents and copyrights (Itami & Roehl, 1991); these invisibles comprise two-thirds of the total GDP of the U.S. (Jhunjhunwala, 2009). With the fast paced advances in information technology, knowledge has now become the major source of competitive advantage for firms as it replaces most of the physical assets and factors of production (Edvinsson & Malone, 1997). According to Moeller (2009), there was a significant change in the resource structure of firms during the late 1990s because firms are now relying more on intangibles instead of physical assets. In the past, these firms used physical assets such as land, buildings, infrastructure facilities and natural resources as their production factors but today modern organisations prefer to mix the intangible resources with physical assets to add more value to the firm (Moeller, 2009).

Intangible assets such as knowledge, innovation capability, and investment in research and development, have dominated the wealth of organisations in the 21st century, which wasn't so for the 20th century when only physical assets determined the wealth of the organisation (Garcia-Parra *et al.*, 2009). The roots of research on intangible assets go back to 1988 to the preliminary work of Colley and Volkan (1988). According to them, goodwill can be defined in two ways. First, goodwill is the capacity of the firm to make abnormal profits. This implies that goodwill can be calculated by discounting the excess earnings of the firm over a certain time period. Second, goodwill can be defined as those assets which are not recorded in the balance sheet and these assets include but are not limited to brand name, patents, relations with customers. Salamudin *et al.* (2010) further divide these intangible assets into two perspectives, *i.e.*, financial and marketing. The financial perspective includes intangibles such as goodwill and copyrights whereas the marketing perspective includes intangibles such as brand name, advertisements and relationships with customers that enable firms to capture a competitive advantage.

The *International Accounting Standard Board* (IASB, 2006) defined intangible assets as: identifiable non-monetary assets which do not have physical existence. Interestingly, firms may still sell, exchange and transfer these assets. In defining the major characteristics of intangible assets, Diefenbach (2006) says that intangible assets are non-physical and can be considered as an idea in the mind rather than on paper. Moreover, these intangible assets are self-renewable once they are used. The typical nature of the intangible assets is that they increase when they are used, e.g., knowledge increases when it is shared with others (Diefenbach, 2006). Nevertheless; the evolution of intangible resources was a breakthrough towards recognizing the existence and importance of intellectual capital.

2.2.2 Evolution of Knowledge Resources

The 1990s decade is an era when firms as well as researchers began to focus on the importance of knowledge workers, especially after the book 2020 Vision by Davis and Davidson (1992) that highlighted the importance of knowledge workers. Knowledge workers are the major assets of firms that use their knowledge to increase the productivity of the firm. Hiebeler (1996) points out that knowledge is a key resource of the firm that should be levered with the passage of the time, which is referred to as effective knowledge management. Aguiar (2009) defines knowledge management as sharing knowledge between different employees and groups within a firm. Knowledge sharing could be beneficial between departments and different business units within a firm, which adds more value than sharing with outside parties like suppliers and customers (Aguiar, 2009).

Physical assets are, most of the time, transferred through different distribution channels but knowledge-based assets can be disseminated without transferring ownership (Brătianu & Orzea, 2009). The transferred knowledge can have more value than the original alone. This idea gave birth to the concept that the dissemination and integration of knowledge should remain a continuous process whereby the firms can come to know “what they already know” and what needs to be added. Curado (2008) argues that knowledge is an integral part of IC that brings new skills and talent to the firm when effectively used with human capital.

2.2.3 Evolution of Intellectual Resources

The concepts of intangible assets and knowledge resources formed the basis of the new concept called “*Intellectual Capital*”. Based on a broader term than intangible and knowledge concepts, IC includes a variety of assets ranging from human resources, copyrights, brand names, goodwill, relationships with customers to organisational culture and databases (Guthrie *et al.*, 2012). As defined by Choong (2008), IC includes all those assets that do not have physical existence but contribute significantly to the value of the firm. Unlike physical assets, which decrease when used, knowledge increases when shared and ultimately increases the value of the IC.

2.3 The Importance of Intellectual Capital for Firms

During the industrial era, physical assets such as plant, property and equipment have been considered the only source of wealth for firms. With the shift of focus from physical assets to knowledge-based resources along with globalization effects, firms now look at knowledge and communication as the strategic resources. This revolution in terms of globalization and knowledge transformation has given rise to the need to recognize and record intangible assets in the financial reports of firms (Cañibano *et al.*, 2000; Pek, 2005; Huang, 2007; Joshi *et al.*, 2013).

The difference between the market value of the firm and its book value verifies the existence of IC, which is not properly recognised on nor is it recorded on the firm's balance sheet. Zambon (2004) argues that annual reports of firms should record all such events that are prone to have an impact on the financial performance of the firm. Despite firms' desire to record IC on their annual reports, strict accounting standards set by some countries prevent IC disclosure on a firm's balance sheet. For example, in Australia, according to the Australian Accounting Standard Board (AASB) 138, for any intangible asset to be eligible to be recorded in the annual report, the assets must be able to be separated from the entity. This rigid characteristic makes disclosure of most of intangibles such as patents, copyrights and goodwill reasonably difficult. Vergauwen *et al.* (2007) argue that costing intangible assets and their expected loss in the form of competitive advantage are major barriers to the disclosure of IC.

In many ways, considering knowledge as the vital resource of a firm, effective management becomes critical in maintaining a competitive edge and the performance of the firm. For example, a firm investing in R&D can create knowledge to be incorporated into its operational processes (Nonaka & Takeuchi, 1997). Vargo and Lusch (2004) argue that companies should strengthen their relationships with customers thereby shifting from physical products to intangibles such as information, knowledge and skills.

2.4 Intellectual Capital Theories

The evolution of IC is based on theories such as the resource based theory, resource dependency theory, which focus on the importance of not only tangible but also intangible assets for modern firms. These theories can be used to link IC resources with the financial performance of firms. This section focuses on some major theories that can be linked to the importance of IC resources and their importance for the competitive advantage of the firms in the developed, emerging and frontier markets of the world.

2.4.1 Resource Based Theory

The resource based (RB) theory is considered the pioneer that focused on the importance of intangible assets for firms (Barney, 1991). The basic argument in this theory is that the competitive advantage of the modern firm should lie in its use of tangible as well as intangible assets. The intangible assets included in this theory should be unique and inimitable which and can build a sustainable competitive advantage for the firm. This theory argues that any firm is a bundle of tangible and intangible resources that depend on each other. This means that the performance of tangible assets depends upon the performance of intangible assets and vice versa.

Physical and intangible assets have long been considered strategic resources for a firm. With the passage of time, the focus of this theory has been mainly dragged towards intangible resources (Reed *et al.*, 2006). These authors argue that it is actually intangible assets or IC capital that contributes more towards a sustainable competitive advantage for firms. They argue that physical assets such as plant, machinery and financial assets are generic and can be substituted at any time by any firm. This argument supports Youndt *et al.* (2004) who conclude that it is only IC that contributes significantly towards value creation and hence builds a sustainable competitive advantage for the firms in the knowledge economy era.

Linking the argument by Kolachi and Shah (2013) with RB theory that IC is important for every small and big firm in developed as well developing countries, we use this theory to explain the relationship between IC and the financial performance of a firm. Based upon this theory, we argue that IC contributes significantly towards the financial performance of a firm regardless of the firm's geographical location, *i.e.,* in all developed, emerging and frontier markets. This argument is consistent with Zéghal and Maaloul (2010) who state that firms can yield extra returns and build a competitive advantage from the effective use of its strategic resources such as IC assets.

2.4.2 Resource Dependency (RD) Theory

The advocates of this theory, Pfeffer and Salancik (2003), argue that every firm depends on several stakeholders such as other firms that hold strategic resources necessary for the operations of the firm. They argue that every firm cannot hold all strategic resources so they have to build long term relationships with those stakeholders who can assist the firm in terms of necessary resources. This necessity actually motivates the firms to engage with the external environment, which forms the basis of social and relational capital for the firms. Linking this theory with the human resources of firms, Abeysekera (2010) argues that firms' effective engagement with the external environment is possible only when a firm holds efficient internal resources such as human capital and learning environment. This argument is also consistent with Williams (2000) who argues that firms should utilize their available human resources effectively to increase the value creation capabilities of the firm.

The resource dependency theory can be analysed from two viewpoints. First, it focuses on the importance of building long term relationships with different stakeholders of the firm so that the firm can deal with any uncertain situations with the assistance from its stakeholders to acquire different resources. Secondly, in continuation of the first argument, this theory recognizes the importance of efficient human resources, which can help the firm to achieve the above mentioned objective, *i.e.,* building relationships with stakeholders. The first dimension of this theory, *i.e.,* "relational capital" is beyond the scope of this study but the second dimension, *i.e.,* human capital, is well within the scope of this current study. So this study can use the theory to analyse the efficiency of human capital especially with regard to its contribution towards a firm's financial performance. Consistent with Williams (2000), we expect the human capital resource of a firm to significantly contribute to value creation by the firm.

2.4.3 Organizational Learning (OL) Theory

Njuguna (2009) argues that a firm should follow a continuous learning process to build a sustainable competitive advantage. This continuous learning is necessary for a firm for many reasons. Firms, for example, can get more know-how about their customers' demands and changing preferences about products. Through continuous learning a firm can bring in necessary innovations in the products and services according to the demands of the market (Goh, 2003). A firm should invest in its resources such as research and development and human resources, which enable a firm to innovate with products. Njuguna (2009) defines organisational learning as the process whereby a firm acquires a new wealth of knowledge that can be translated into innovation and can be protected in the form of unique process, models and copyright.

Since these resources (a firm's unique production processes, software, copyrights) are great source of competitive advantage for the firm so the firm should follow a learning curve to build on these resources (Njuguna, 2009). In the literature, these resources have been termed structural capital in many studies (Stewart & Ruckdeschel, 1998; Choong, 2008) so this theory can be used to explore the role of structural capital in value creation of a firm. Recognising the importance of structural capital for firms, this study uses organisational learning theory to explore the role of structural capital as an important element of IC, in the financial performance of firms in developed, emerging and frontier markets of the world.

2.5 Advantages in the Measurement of Intellectual Capital

The main purpose of this study is to evaluate the importance of IC in value creation of firms to justify investment in IC. As argued by Kannan and Aulbur (2004), the major aim in measuring IC is to explore the value of hidden assets and develop those assets to help to achieve a firm's goals. The importance of IC measurement can be seen in the statement, "what you can measure, you can manage, and what you want to manage, you need to measure" (Roos *et al.*, 1997). The following advantages of IC measurement have been explored in the literature (Guthrie & Petty, 2000; Menor *et al.*, 2007; Čater & Čater, 2009; Zangoueinezhad & Moshabaki, 2009).

- IC measurement helps to identify the real value of intangible assets.
- Evaluation of IC helps to identify the true pattern of knowledge flow within firms.
- Learning patterns of firms will accelerate by effective IC measurement.

- IC measurement, from time to time, will help monitor the intangible assets and explore new methods to increase the value of these intangibles.
- IC measurement helps in understanding and enhancing a firm's relationships with different stakeholders such as customers.
- IC measurement can help increase investment in R&D, which will enhance innovation in products and services.
- IC can increase knowledge sharing activities among the employees and firms once the benefits of knowledge management are realized.
- Measurement and effective management of human capital, one component of IC, will increase the motivation of employees.

2.6 Empirical Studies on IC and Financial Performance

A number of studies have been conducted both regionally and cross border to measure the efficiency of IC and its impact on a firm's financial performance. These studies have focused on almost all industries from banking to textiles because IC is important for most industry types (Pek, 2005; Gan & Saleh, 2008; Young *et al.*, 2009; Clarke *et al.*, 2011; Kamal *et al.*, 2012; Joshi *et al.*, 2013; Lu *et al.*, 2014). In line with the objectives of this study, we review the literature on the efficiency of IC and its relationship with a firm's financial performance in developed, emerging and frontier economies.

2.6.1 IC and Firm Performance in Developed Economies

Firms in the service industries such as banking and finance, rely heavily on knowledge-based resources. A major portion of these firms' output comes from the ability of employees to use knowledge effectively to solve clients' problems. Although physical capital is important for any business to operate, IC is also crucial for firms to achieve their goals (Pek, 2005). Furthermore, Young *et al.* (2009) argue that managers of firms in general and banks in particular should recognise the brain power of their employees as the major source of revenues and should invest in the training and development of their employees. A similar argument presented by Karatepe and Uludag (2008) is that extensive investment in training and development programmes for employees can increase the quality of services for customers.

Sydler *et al.* (2014) find that all three factors of IC, *i.e.*, human capital, R&D (structural capital) and relational capital, play significant roles in the value creation of firms. Using a residual income model on 69 pharmaceutical firms from Bloomberg for the period of 2002 to 2009, they conclude that investment in R&D and advertising creates IC in subsequent years, which leads to higher returns on assets. The authors further argue that these three elements of IC, *i.e.*, human, structural and relational capital, also influence each other. For example, if a firm wants its promotional activities to create IC efficiently then the firm should increase the quality of its products through proper R&D (structural capital) and skilled personnel (human capital). Similarly, Gupta and Roos (2001) argue that value creation should be dynamic enough that each factor can interact with the others. For example, having a strong database is not sufficient unless the firm has skilled employees to make efficient use of that database (Marr *et al.*, 2005)

Clarke *et al.* (2011) argue that the role of IC in the value creation is equally important in developed countries as in emerging or frontier countries. The authors studied the impact of IC on the financial performance of firms in Australia and find that IC efficiency (VAIC) is directly related to the financial performance of the firms, especially in terms of human capital and physical capital efficiency. Using annual report data of Australian publicly traded firms from 2003 to 2008, Clarke *et al.* (2011) measure the efficiency of IC and its relationship with the financial performance of firms. Four performance measures, ROA, ROE, revenues growth and employee productivity, were used in their analysis. The results show that, despite the growing importance of IC for firms, physical capital still dominates the financial performance of firms in Australia. These results are contrary to those of Mavridis (2004) study in Japan where banks efficient use of human resources was superior in terms of financial performance and physical capital is least important. An important finding of Clarke *et al.* (2011)'s study is that investment in human and structural capital in the previous year accelerates value creation in the current year.

IC is increasingly replacing physical assets' importance in value creation not only for firms but also at country level as illustrated by Kaplan and Norton (2004). The authors argue that, some countries such as Venezuela and Saudi Arabia, are rich in natural resources but have made poor investments in human capital hence produce a very low output per person. On the other hand, some countries such as Singapore and Taiwan, which are not rich in natural resources, have made significant investment in human capital and produce far greater output per person. Using data from the annual reports of public traded companies in Taiwan from 1992 to 2002, Chen *et al.* (2005) measure the efficiency of IC using VAIC model and the impact on the financial performance of firms. The authors find that IC is positively associated with the market value and financial performance of firms. Further analysis reveals that individual components of VAIC, *i.e.*, human, physical and structural capital, exhibit varying degrees of correlation with the dependent variables suggesting that investors may give different weighting to each of the IC components. Chen *et al.* (2005) use R&D and advertising costs as additional variables and conclude that these two variables capture additional information that might be missing in the original VAIC model.

The role of IC is vital in high-tech firms especially for innovation in products (Shiu, 2006). The author investigated the efficiency of IC and its relationship with a firm's financial performance in 80 high-tech firms in Taiwan for the year 2003. The results revealed that VAIC has a significant positive correlation with return on assets (ROA) and market to book (M/B) ratio but a negative correlation with assets turnover. Shiu (2006) suggests that these high-tech firms can transform IC into high value added products. Moreover, Hsu and Wang (2012) measured the efficiency of IC in high-tech firms in Taiwan over the period 2001 to 2008. The authors use Dynamic Capability[10] (DC) as a mediating variable. Their results reveal that dynamic capability is a strong mediator of the relationship between structural capital and a firm's financial performance but the effect of human and relational capital on financial performance is not fully mediated by dynamic capability.

Intangible assets are more important than tangible assets for value creation in IT industry since the quality of output depends on innovation (Wang & Chang, 2005). The authors investigated the relationship between IC and firm performance in the Taiwan IT industry. Using data from *Taiwan Electronic Journal* (TEJ) for listed firms in Taiwan's IT industry, the authors use the Partial Least Squares (PLS) approach to measure the relationships. Their results reveal a significant positive relationship between IC elements and a firm's financial performance. Human capital is indirectly correlated with the other three elements of IC, namely, customer capital, innovation capital and process capital. This indirect effect shows that investment in human capital can trigger the efficiency of the other elements of IC, which in turn increases value added for the firm.

Realizing the important role of IC in today's economy, countries around the world are setting their goals to include the enhancement of IC efficiency. As argued by Tan *et al.* (2007), Singapore has set as its objective to make the country an important centre known as a *knowledge-based economy*. The authors analysed the efficiency of IC and its impact on the financial performance of firms in Singapore. Selecting 150 companies from the Singapore stock exchange, the data were drawn from the annual reports for the years 2000 to 2002. The study categorized all 150 firms into (a) manufacturing firms (b) trading firms (c) service firms and (d) property related firms. The purpose of this classification was to critically analyse differences in the IC efficiency of different industries. VAIC was used to measure IC and three financial ratios were used as performance measures: return on equity, earnings per share and annual stock returns. Their results reveal that a firm's financial performance is positively correlated with IC in terms of VAIC. Tan *et al.* (2007)'s study is the first to analyse the relationship between growth rate of IC and a firm's financial performance. They find a positive correlation where the growth rate of IC was calculated as the increase in the value of IC from one year to another. An important finding of this study is that the impact of IC on a firm's financial performance varies significantly from industry to industry. The authors suggest that managers in

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[10] Dynamic Capability is defined as the ability of the firm to accumulate knowledge through continuous learning process.

knowledge intensive industries should realize the importance of IC and increase investment in IC to gain a competitive advantage.

An empirical study based on high-tech industries, traditional industries and service industries was conducted by Zéghal and Maaloul (2010). The purpose of the categorization of industries was to test whether the role of IC in value creation differs from industry to industry. The authors used VAIC to measure the efficiency of IC for data obtained from *Value Added Scoreboard* (VAS) issued by UK DTI[11] for 300 firms listed on London Stock Exchange (LSE) for the year 2005. The study used three different aspects of a firm's performance: (a) economic performance measured as operating income to sales ratio; (b) financial performance measured as ROA; and (c) market valuation measured as the M/B ratio. The results reveal that VAIC is significantly, positively correlated with the economic performance of firms, which implies that IC can help to reduce production costs for firms (Zéghal & Maaloul, 2010). VAIC was also significant and positively correlated with ROA, which implies that IC plays a significant role in value creation for shareholders as well as other stakeholders such as creditors, suppliers and government. Zéghal and Maaloul (2010)'s results support the argument that the role of IC differs across different industries. The authors suggest that future research should increase the time period and should revisit some basic assumptions of the VAIC model to validate the results.

2.6.2 IC and Firm Performance in Emerging Economies

Knowledge is a major resource of firms and its creation is critical for the firms to gain a competitive advantage for firms, especially in emerging economies (Spender & Grant, 1996; Argote & Ingram, 2000). Firms can achieve this goal by increasing their investment in R&D and training and development programmes. These investments enhance the firms' ability to absorb and disseminate new knowledge effectively (Deeds & Decarolis, 1999). Furthermore, firms can acquire new, highly qualified personnel who will increase the present levels of knowledge in the firm. Another way to enhance knowledge-based resources is by knowing consumers' perceptions of the firms' products, which allows the firm to follow the learning curve to innovate its products (Leslie, 2006).

Bharathi Kamath (2008) investigated the efficiency of IC and its relationship with the financial performance of firms in the Indian pharmaceutical industry. Using annual data for 10 years (1996-2006), the author used VIAC to measure the efficiency of IC. The results reveal that domestic firms are relatively more efficient in using IC. The results also reveal that only human capital is closely associated with the profitability and productivity of the firm in terms of ROA and assets turnover, respectively. The author argues that since the study is a time series further analysis in terms of a cross-section study may improve the results. In a similar study, Sharabati *et al.* (2010) examined the

[11] UK Department of Trade and Industry

relationship between IC and business performance in Jordan. The results show that IC significantly positively influences the financial performance of firms.

In a knowledge driven economy, IC has become the major source of value creation for services industries such as banks where bank management determines the quality of services being offered (Bontis, 2001). In this regard, Pek (2005) used VAIC as a measure of IC to study the efficiency of IC in the Malaysian banking sector. The study sample included both foreign and domestic banks in Malaysia. The results reveal that banks show higher human capital efficiency than structural capital efficiency. In addition, foreign banks are more efficient in using IC than domestic banks and investment in IC yields higher returns than investment in physical capital. The author argues that banks can benchmark the efficiency of IC among themselves to improve the utilization of IC in the future. Kamal *et al.* (2012) examined the efficiency of IC and its association with the financial performance of 18 commercial banks publicly traded in Malaysia and finds different results from those of Pek (2005). Kamal *et al.* (2012) find only physical capital is significantly positively correlated with a firm's performance. Surprisingly, human capital efficiency was negatively correlated with ROA and ROE, which means that an increase in human capital efficiency leads to a decrease in ROA and ROE, which contradicts the basic theory of IC. The differences in the results for the same industry in Malaysia may be attributed to the small sample size. Kamal *et al.* (2012) indicate that some independent variables that could better explain the variation in a firm's financial performance were omitted in their study.

Yalama and Coskun (2007) investigated the role of IC in value creation for the banks listed on the Istanbul stock exchange (ISE). The authors measured the performance of IC using the VAIC model for banks listed on the ISE for the period 1995-2004. The preliminary analysis revealed that all banks differ in utilizing IC efficiently. The authors then used Data Envelopment Analysis (DEA) to test the effect of IC on the financial performance of the banks. Their results reveal that IC is a more important driver in value creation than physical capital. The authors recommend that banks should effectively manage IC to generate above average returns.

Ting and Lean (2009) studied the impact of IC on the financial performance of financial institutions in Malaysia. Data from annual reports of Malaysian financial institutions were used to measure IC for the period 1999-2007. The results reveal that VAIC is significantly positively correlated with a firm's financial performance in terms of ROA. Further analysis of the individual components of VAIC shows that human and physical capital significantly contribute to the added value. Structural capital, however, shows a negative relationship with profitability. The authors argue that in a knowledge-economy, investors also need information about non-financial aspects of the company when making investment decisions thus disclosure of IC related information on the balance sheet of firms is now required (Li *et al.*, 2012). Muhammad and Ismail (2009) investigated the relationship of IC and financial performance in Malaysian banks. Their results reveal that VAIC (as a measure of IC efficiency) is significantly correlated with profitability. Further industry level analysis reveals that the banking sector relies more on IC than insurance and brokerage firms. Individual components of VAIC, *i.e.*, HCE, CEE[12] and SCE, however, did not show any significant relationship with either the profitability or productivity of the firms, which means that investors do not place separate the weights on individual components of VAIC. The authors argue that this disparity in results (between VAIC and its individual components) may be attributed to the small sample size since the study investigated only 18 banks.

Joshi *et al.* (2013) studied the efficiency of IC in the Australian financial sector and report that VAIC is significantly correlated with human costs and performance of banks. The authors selected 33 financial firms including investment banks, insurance companies and diversified financial companies for the period 2006 to 2008. Their results reveal that, in the Australian financial sector, IC efficiency is highly dominated by human capital. Similar results were reported by Pek (2005) and Joshi *et al.* (2010) where human capital was the major contributor to a firm's value creation and higher market returns (Pantzalis & Park, 2009). Joshi *et al.* (2010) also report that investment companies in Australia rely more heavily on human capital than investment banks or insurance companies. Insurance companies however, rely more on physical capital.

Lu *et al.* (2014) argue that the insurance industry relies heavily on the knowledge and skills of the employees who bring innovation into the services offered by the firms. The authors analyse the efficiency of IC and its impact on the financial performance of firms in the Chinese life insurance industry. Using data from annual reports of life insurance companies from 2006 to 2010, the authors used the dynamic slack based model to measure the efficiency of IC and its relationship with the financial performance of the firms. Contrary to Joshi *et al.* (2010)'s study, the results of Lu *et al.* (2014)'s study reveal that the efficiency scores of IC in insurance companies are stable over the study period. Further analysis shows a significant positive relationship between IC efficiency and a firm's financial performance, which supports the argument that IC plays a vital role in value creation in insurance firms.

Gan and Saleh (2008) analyse the efficiency of IC and its relationship with corporate performance in technology-intensive firms in Malaysia. The study shows that technology-intensive companies still rely heavily on financial capital for value creation. Further analysis shows that investors may give a different value to individual components of IC but physical capital remains the most important factor in value creation for these firms. The study finds a weak relationship between VAIC and the

[12] Pulic (2000) use this term "capital employed efficiency" for total capital of the firm.

profitability and productivity of the firms but no relationship between VAIC and market value of the firms. These results are similar to those of Firer and Williams (2003) but Gan and Saleh (2008)'s study focused only on companies listed on MESDAQ (*Malaysian Exchange of Securities Dealing and Automated Quotations*), which does not reflect all companies traded on the Bursa. Another possible reason for this weak relationship could be the study's limited time period (2004-2005). A similar study by Ahangar (2011) on IC performance and its association with profitability, sales growth and employee productivity, documents that among individual components of IC, only human capital shows a significant relationship with a firm's financial performance. The author reports that the impact of IC on the financial performance is mediated by the competitive advantage of the firms.

The concept of IC is still very new in emerging markets as argued by Vishnu and Kumar Gupta (2014) and Razafindrambinina and Anggreni (2008) who studied the impact of IC on a firm's financial performance in India and Indonesia, respectively. The authors find that IC is significantly correlated with the overall financial performance of firms with the exception of revenue growth. Both studies confirm the argument that physical capital plays a vital role in value creation of firms in developing countries. Appuhami (2007) reveals that IC significantly influences the stock performance of Thai firms in terms of capital gain. This relationship reveals that effective management of IC can also directly increase the shareholders' wealth, which may help the firm to attract new investors.

In a cross-industry study, Pal and Soriya (2012) analyse the efficiency of IC in the pharmaceutical and textile industries in India. The authors use the VAIC model to measure the efficiency of IC. The results show a positive relationship between IC and the profitability of firms measured in terms of ROA. Surprisingly, no correlation was found between IC and the ROE of firms in either industry. In a similar study by Bollen *et al.* (2005) on the efficiency of IC in the pharmaceutical industry in Germany, the authors find a positive relationship between IC and ROE. The different results may be attributed to the economic development stage of the countries.

The software industry is known as an IC intensive industry where the output mostly depends on the creativity of human skills (Kweh *et al.*, 2013). These authors measured the efficiency of IC and its impact on the financial performance of firms in the software sector of Malaysia. The study's sample included all 25 firms in the software sector listed on Bursa Malaysia. Individual components of VAIC were used as inputs in the DEA with ROE and Tobin's Q as output variables for a firm's performance. The results reveal that firms listed on ACE are more efficient than those on Bursa in terms of IC. Human capital was, however, the major contributor towards value creation in all firms, which supports the argument that IC plays an important role in value creation. Kweh *et al.* (2013) conclude that firms in the software industry should understand the value of IC and effective management to achieve competitive advantage.

In a knowledge driven economy, the use of traditional performance measures, which are prey to conventional accounting rules in defining income, are perhaps inappropriate (Firer & Williams, 2003). The authors argue that the use of these measures provides wrong or insufficient knowledge to investors in decision making. The authors further raise two questions: (a) why do these traditional accounting standards restrict the reflection of IC in financial measures knowing that knowledge is a key to the firm's success? And (b) if financial measures are mainly used by managers to make decisions then what measuring system will be more suitable in this knowledge driven era?

To address these issues, Firer and Williams (2003) analyse the relationship between efficiency of IC (VAIC) and the firm's financial performance in terms of profitability, productivity and market-to-book value. The authors use firm size, leverage, ROE and industry type as controlled variables to capture their effects. Using data drawn from the annual reports of 75 publicly listed firms on the Johannesburg stock exchange (South Africa) for the year 2000, the authors used VAIC to measure IC efficiency. Despite numerous studies reporting a strong positive correlation between IC and a firm's financial performance, Firer and Williams (2003) report inconclusive results. There is only a moderate relationship between structural capital and profitability. Surprisingly, the authors' study reports a negative relationship between human capital efficiency and productivity measured in terms of assets turnover. According to authors, these inconclusive results may be attributed to the limited number of firms and only one year time period used in the study. Firer and Williams (2003) suggest that further research is required to better understand the relationship between IC and the financial performance of firms especially in emerging economies.

In a recent study on IC efficiency and its impact on financial performance of pharmaceutical firms in India, Vishnu and Kumar Gupta (2014) extended the original VAIC model by including a new variable called *relational capital* (RC). The authors' results show a positive relationship between IC and firm performance but the new variable RC fails to produce any significant relationship. ROA is the preferred dependent variable over ROS (Return on Sales). Vishnu and Kumar Gupta (2014) however, suggest adding more variables to the VAIC model and using new proxies to measure the variables. The authors also suggest adding more industries and countries to generalize the results because their study was limited to 22 firms in the Indian pharmaceutical industry.

Chan (2009b) analysed the relationship between IC and a firm's financial performance in Hong Kong. The author includes all the firms listed on the Hong Kong stock exchange and uses annual reports data for the period 2001 to 2005. The study uses the VAIC model to measure IC efficiency. Chan's results reveal only a moderate correlation between IC efficiency and the financial performance of firms in terms of profitability. Physical capital remains the major contributor to value added in Hong Kong firms. These results are consistent with Firer and Williams (2003). Moreover, Chan (2009b) argues that Hong Kong is lagging behind its competitors such as Singapore and Taiwan in the development of IC. The author recommends that policy makers in Hong Kong should pay more attention towards the cultivation of IC to compete in today's knowledge driven economy.

Şamiloğlu (2006) studied the relationship between IC efficiency 'measured in terms of VAIC' and market valuation of the firms measured as the M/B ratio. The study uses annual reports data for all banks listed on the Istanbul stock exchange for the period 1998-2001. The author's results show no significant relationship between VAIC and the market value of a firm. Similarly, Maditinos *et al.* (2011) measured the efficiency of IC and its impact on the financial performance and market value of firms listed on the Athens stock exchange. Using annual report data for the period 2006-2008, the study reveals no significant relationship between VAIC and market value and firm financial performance. However, the authors argue that these results are not surprising because of some alarming characteristics of the Greece economy, such as the low level of foreign direct investment, an inefficient capital market and huge public sector holdings, which may have caused the low IC efficiency.

Based on these results, Maditinos *et al.* (2011) raised some concerns about the research methodology as well as the consistency of results using VAIC. First, as far as the research methodology is concerned, the authors argue that the use of the M/B ratio might be inappropriate because it is highly influenced by the investor sentiment in the market. Second, linking IC to market valuation might be incorrect because sometimes the market value goes down because of external forces such as investors' perceived risk. Third, calculating the market value of firms based on the stock price at the end of the year might not be a true representation of the price throughout the year. The authors recommend using the VAIC model to measure IC efficiency in developed and frontier economies to check the consistency of the results.

2.6.3 IC and Firm Performance in Frontier Economies

Despite increasing effort to measure and manage IC efficiently in developed economies and, to some extent, in emerging economies, the concept of IC is still in its initial stage in developing[13] countries (Bharathi Kamath, 2008). Mehralian *et al.* (2012) studied the performance of IC and its impact on the financial performance of firms in Iran's pharmaceutical industry. The results reveal that IC is weakly associated with the profitability of firms but there is no association between IC and productivity and market valuation of the firms. The authors checked robustness through applying an Artificial Neural Networks (ANN) model and report same results. Physical capital is found to be the major contributor towards value creation as is expected from most of the studies in frontier economies.

[13] As per the MSCI index, the majority of the developing countries are classified as frontier countries.

Mehralian *et al.* (2012) argue that the strong association between physical capital and firm performance is because the Iranian pharmaceutical industry is still underdeveloped. Conversely, no association between firm performance and HCE or SCE shows little or no investment in: (a) training and development programmes for employees, (b) improper advertising and marketing strategies, and (c) a low level of research and development. Mehralian *et al.* (2012) suggest that managers in such a knowledge-intensive industry should realize that their future growth depends on innovation in the products that can be achieved only through efficient structural capital and well trained human resources. The small number of firms included was, however, the major limitation of the research and its findings.

The first study investigating the efficiency of IC and its impact on the financial performance of Islamic banks was by Rehman *et al.* (2011). Using annual report data of Mudarba firms listed on the Karachi Stock Exchange, the authors used the VAIC model to measure IC efficiency. The results reveal a strong association between IC and financial performance of Islamic banks in Pakistan. The results also reveal that human capital is the major contributor towards value added for the banks. All individual components of VAIC, i.e., HCE, SCE and CEE, are significantly correlated with the financial performance of Pakistani Islamic banks. These results support the notion that sufficient investment in IC and efficient management can contribute significantly towards value creation in firms in an underdeveloped country such as Pakistan.

2.6.4 IC and Firm Performance: Cross-Country Comparisons

IC efficiency differs significantly across borders because of different levels of economic development and different environments in which employees work (Gigante, 2013). In a cross-country study on IC efficiency and its impact on the financial performance of banks in selected European countries, Gigante (2013) finds that IC efficiency varies significantly among banks from the sample countries[14]. The study uses data from the annual reports of 64 selected banks from nine European countries for the period 2004 to 2007. The study finds that the mean IC efficiency scores for Finnish banks are highest, *i.e.* 12.23, and 1.88 for German banks being the lowest. Further analysis shows that human capital efficiency for banks in Finland is again the highest. The study reveals that IC efficiency is significantly correlated with the financial performance of banks in terms of ROA and ROE. However, there is no correlation between IC efficiency and market valuation in terms of the M/B ratio of the banks. The author recommends further study to include more banks and increase the time span to generate more robust results.

Young *et al.* (2009) argue that banks play an important role as intermediaries by mobilizing funds from depositors to households and businesses; human resources play a significant role in this

[14] Countries include Czech Republic, Denmark, Finland, Germany, Italy, Norway, Poland, Spain, and Sweden.

transfer. The authors did a cross country comparison of eight Asian economies[15] measuring the IC efficiency in banking. Using banks' financial reports data from 1996 to 2001, the authors use the VAIC model to measure IC efficiency in eight Asian countries. The authors find that both human and financial capital play significant roles in value creation of banks. Following the 1997 Asian financial crisis, the authors find that the ability of human capital to create value was negatively affected during financial turmoil, making human capital a most vulnerable resource during uncertain environments.

2.7 Summary of the Empirical Studies

The importance of IC was realized by developed countries in the late 1980s and early 1990s when IC became the focus of the research and business communities. Since then, a number of attempts have been made both at firm level and individual researchers to develop appropriate models to measure IC. The Skandia Navigator model developed by Edvinsson and Malone (1997) was among the pioneers to recognize and measure IC. The purpose in developing this model was to increase the importance of IC to include its disclosure on the balance sheet. Among the limited empirical studies (Guthrie & Petty, 2000; Maditinos *et al.*, 2011; Gigante, 2013; Joshi *et al.*, 2013) on IC and firm performance in developed economies, most studies support the argument that IC plays a vital role in value creation of firms. However, these studies have several limitations such as a small number of firms included in the sample and a short study period. The concept of IC is still very new in emerging economies. Despite of the number of studies[16] on IC and firm performance in emerging economies, the results are inconclusive. Some studies, such as Young *et al.* (2009), show a positive relationship between IC and firm performance but other studies, such as Firer and Williams (2003), find no relationship.

This inconsistency in results from emerging economies is mostly attributed to different factors, such as the level of economic development of the economy, the lack of available data and the limited scope of the studies in terms of time period and number of firms studied. In addition, Ståhle *et al.* (2011) criticise the construction of the VAIC model, in general, and its structural capital measure, in particular. The VAIC model ignores some key elements of IC, such as relational capital and social capital. Nonetheless, most researchers emphasize the necessity to recognize the importance of IC as a vital contributor to value creation for firms. IC is a key factor in value added for firms during financial crisis in Young *et al.* (2009)'s study. The authors suggest that further research on the role of IC in financial crises should be tested to determine if IC plays a significant role in saving troubled firms.

[15] The list of Asian countries is: Hong Kong, Indonesia, Malaysia, Philippines, Singapore, South Korea, Thailand and Taiwan.
[16] See, for example: Vishnu and Kumar Gupta (2014), Bharathi Kamath (2008), Kamal *et al.* (2012), Ting and Lean (2009).

Surprisingly, some studies[17] on IC and firm performance in frontier countries produce a strong positive relationship. Few studies (Mehralian *et al.*, 2012), however, find a very weak or no relationship between IC and firm performance. This disparity in results is again attributed either to differences of industries or lack of available data, which has always been a problem in most under-developed countries. Another reason for this weak or no relationship is the low level of investment in employees since most businesses are owned or managed by one person in frontier economies such as Iran and Pakistan. Despite strong efforts to make full use of IC in developed economies and, to some extent, in emerging economies, IC still needs to be explored in emerging and frontier economies (Bharathi Kamath, 2008).

2.8 IC Measurement Models and Conceptual Framework

This section outlines and discusses monetary and non-monetary models used in the literature to measure IC efficiency. This section also outlines the conceptual framework used in this study along with the monetary based VAIC model to measure IC efficiency.

2.8.1 IC Measurement Models

The RBV of a firm holds that a firm's intangible assets contribute equally towards the financial performance as its tangible assets and VA should be recognized as a measure of performance rather than the return to owners. VA augments the true measure when it comes to an economy's production in today's knowledge-based economy (Sveiby, 1997). Firer and Williams (2003) argue that different perceptions of accounting income have led to different performance measurements based on different theories. For example, under the enterprise resource perspective, an organization acts as a decision making unit on behalf of its stakeholders including employees, shareholders, and creditors, and the profit, the reward for these stakeholders is termed value added.

In accordance with the different theories on a firm's income, different models have been introduced in the literature to measure IC efficiency. These models can be classified into two broad groups, *i.e.*, monetary and non-monetary. Table 2 summarizes these models.

[17] See, for example: Rehman *et al.* (2011).

Table 2.1 Monetary and Non-Monetary Models Used to Measure IC

Monetary Models	Non-Monetary Models
Market Capitalization models • M/B value model • Tobin's Q by Luthy (1998) **ROA models** • EVA[a] & MVA[b] models by Bontis (1999) • Calculated intangible value by Dzinkowski (2000) • VAIC by Pulic (1998) • Intangible driven value model by Lev (2000) • Residual income model by Ohlson (1995)	**Scorecard models** • Balance scorecard by Kaplan and Norton (1995) • Technology broker model by Brooking (1996) • Skandia Navigator by Edvinsson and Malone (1997) • IC-Index model by Roos *et al.* (1997) • Intangible assets monitoring model by Sveiby (1997) • Heuristic frame by Joia (2000)

[a]Economic value added
[b]Market value added

2.8.2 The Evolution of Prominent IC Models and the Conceptual Framework

The *Skandia Navigator* model is among the pioneers acknowledging the importance of IC and its disclosure on the balance sheet. The model classifies IC into four elements namely human, process, renewal and customer capital.

Kaplan and Norton (1995) propose an IC measurement model known as the *Balance Score Card*. The idea was to measure the efficiency of intangible assets which were previously ignored. This model produces results in the form of scores for different elements of IC such as human, structural and innovation capital. Using Skandia Navigator as a base, Bontis (2004) constructed a new measure called *National Intellectual Capital Index* (NICI) aimed at measuring and managing IC at the national level. The model includes market capital, process capital, renewal capital and human capital as different indicators of the IC of a nation. The author applied NICI model to several Arab countries to measure the national IC and concludes that national IC represents almost 20 percent of the total financial wealth of each country in the study's sample.

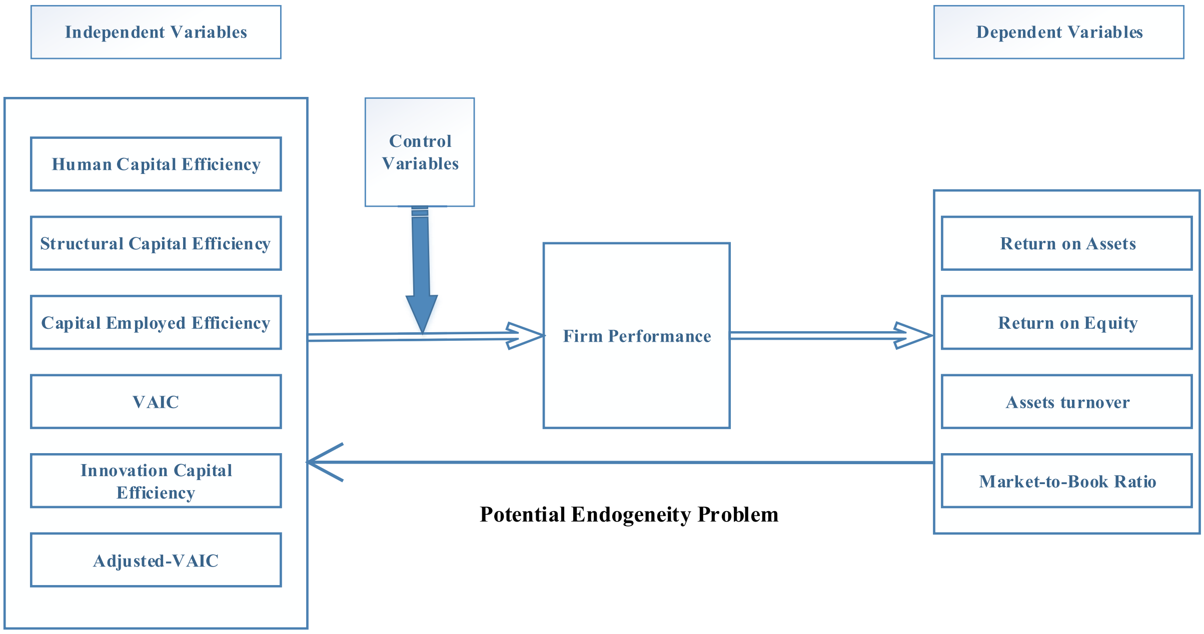
Based partially on the Skandia Navigator framework, Pulic (1998) developed a new but more comprehensive, easy to calculate measure called *Value Added Intellectual Coefficient* (VAIC). The VAIC model is unique since it measures the IC size and efficiency thereby giving a base for comparison between firms, industries and economies (Pulic, 1998). Unlike previous models, which are either customized or fit for some specific profile of firms, the VAIC model uses data from audited reports of firms, which increase its authenticity (Pek, 2005).

The VAIC model has been extensively used in the literature to measure IC efficiency. For example, Chen *et al.* (2005) used the VAIC model to study the relationship between IC and a firm's financial performance in Taiwan and reports a significant positive relationship. Firer and Williams (2003), studying the relationship between IC and a firm's financial performance, found the relationship to be limited and mixed. The VAIC model has been extensively used in previous studies (Tan *et al.*, 2007, 2008; Ting & Lean, 2009; Hsu & Wang, 2012; Pal & Soriya, 2012; Joshi *et al.*, 2013; Kweh *et al.*, 2013; Sumedrea, 2013; Berzkalne & Zelgalve, 2014; Lu *et al.*, 2014; Vishnu & Kumar Gupta, 2014) because of its usefulness and ease of understanding. Following the aforementioned studies and the unique characteristics of the VAIC model, we use it to measure IC efficiency. The VAIC model has several benefits. For example, the results of the model provide a basis for comparison of IC efficiency across firms. The VAIC model uses publicly available data from annual reports of firms, which minimizes the risk associated with the results' authenticity (Pek, 2005).

Since the main objective of this current study is to measure IC efficiency and its impact on firm performance, we use the VAIC model and its individual components, *i.e.*, human, structural and physical capital, to measure IC efficiency along with the performance of individual components. This study uses ROA, ROE, assets turnover and P/B as firm performance measures. Departing from previous studies, this study replaces the structural capital measure of the VAIC model with innovation capital[18] and introduces an adjusted-VAIC model to overcome criticism of the VAIC model. Figure 2.1 outlines the basic conceptual framework of this study.

[18] This is discussed in details in chapters 3 and 6 of this study.

Figure 2.1 Conceptual Framework of the Study



The above framework measures the impact of IC efficiency (VAIC) along with its individual components, *i.e.*, human, structural and physical capital efficiencies, on firm performance. Hence, IC and individual components are independent variables and firm performance is a dependent variable. Control variables such as GDP growth and firm size are also included to measure their impact on this relationship. It is worth mentioning here that a backward arrow from firm performance to IC shows the existence of potential endogeneity problems that are further investigated and mitigated in chapter 5.

Chapter 3

Research Methodology

3.1 Introduction

This chapter outlines the research methodology used in this current study. Section 3.1 discusses the VAIC model, the advantages, calculations and interpretations of the model. Section 3.2 presents the adjusted-VAIC model after making necessary adjustments in the original VAIC model. Section 3.3 defines the dependent variables and their measures and section 3.4 discusses the regression models used in this current study. Section 3.5 discusses the sample including markets, firms, data collection and data transformation. Finally, section 3.6 summarizes the chapter.

3.2 Monetary Measure of IC: the VAIC Model

Several models are in the literature that can be used to measure IC efficiency. These models can be broadly categorized into two categories: monetary and non-monetary measures (Edvinsson & Malone, 1997). According to Sydler *et al.* (2014), non-monetary models (qualitative) limit benchmarking and provide limited information because of a company's specific characteristics. It is more challenging when there are no set guidelines regarding the disclosure of IC by companies. Cheng *et al.* (2008) classify IC research into *survey questionnaire* and *financial data* methods. The former approach uses a survey questionnaire to ask respondents to rate their agreement on a 5 point Likert scale. This indirect method contains several questions depending upon the purpose of the study and measures the relationships between the respondent's behaviour and the results (Bontis, 2001; Cabrita & Vaz, 2005; Martínez-Torres, 2006). The latter approach however, uses financial data obtained from the financial reports of firms. Monetary based models allow users to compare firms or industries and sometimes countries. Another benefit from using quantitative models is that these models use publicly available information, usually audited that increases the reliability of the results. This current study uses the quantitative approach because of these validation features and the ability to compare results across firms or countries.

One of the most widely used monetary measures is *Value Added Intellectual Coefficient* (VAIC) developed at the Austrian Intellectual Capital Centre (Pulic, 1998, 2004). The VAIC model measures the value added by the business along with individual contributions of each asset category towards the firm's value. These asset categories include tangible and intangible assets such as intellectual resources. Unlike other assessment-based measures that are unable to measure the asset value of IC of a firm, VAIC is an indicator-based measure that uses financial report data and calculates the asset value and IC efficiency of a firm, which is useful for decision making by management. This study adopts the VAIC model because of its unique benefits discussed below.

3.2.1 Advantages in using VAIC model

The literature (Firer & Williams, 2003; Pek, 2005; Chan, 2009a; Joshi *et al.*, 2013) provides the following benefits from using VAIC model to calculate IC efficiency:

- ✓ The VAIC model results in numerical indicators that are equally important for all stakeholders such as creditors, investors, customers, shareholders, providing them the basis for comparing the components of IC.
- ✓ Unlike other measures, which demand scores or grading award criteria, VAIC is a quantitative measure that uses statistical analysis and computations for a large number of companies covering millions of data items collected over time.
- ✓ Because of the quantitative measurement, VIAC results can be compared with traditional financial measures such as turnover ratios and profitability ratios that are found in firms' financial reports.
- ✓ VAIC is a simple measure in terms of computational procedures and is easy to understand by management and other stakeholders who are familiar with corporate financial information.
- ✓ According to Chan (2009a), the VAIC model can be consistently applied and its results can be compared at departmental, firm, industry and country level thereby providing a benchmark for effective IC management.
- ✓ Using publicly available information from audited financial reports increases the reliability and effectiveness of the results.
- ✓ The VAIC model is based on a value added approach that is consistent with the RBV of the firm, which highlights the importance of IC for the firm.
- ✓ The VAIC model has been used rigorously to measure the efficiency and effectiveness of IC of publicly listed companies in a number of countries such as Australia, Taiwan, Malaysia, India, Austria, Pakistan and UK (Chan, 2009a).

3.2.2 Calculations of VAIC

This section discusses in detail how the VAIC model works and what steps are involved in the calculations of VAIC. The VAIC calculations involve a two-step process (Pulic, 1998) where value added is calculated in the first step and VAIC is calculated in the second step.

Step 1

In the VAIC model, total *Value Added* (VA) by the business can be calculated as:

$$VA = OUT - IN..........(3.1)$$

Where VA is value added, OUT is output, which represents the total revenue of a firm earned by selling its products or services. IN is input, which includes all expenses a firm makes in raw materials, operational overheads. Pulic (1998) did not include staff costs as expenses in the VAIC model. The author argues that since this money is spent on employees who play a major role in the value creation process, therefore these expenses should be treated as an investment. By replacing output and input with their individual variables in equation 3.1, we can write equation 3.2 as follows:

$$VA = R - C........(3.2)$$

Where R is total revenues, C is total material cost incurred during the year. Equation (3.2) can also be written as:

$$VA = NI + LC + I + T + DP.........(3.3)$$

Where NI is net income for the year, DP is depreciation and amortization, LC is labour cost, I is interest cost and T is taxes.

Net income can be calculated as:

$$NI = R - C - DP - LC - I - T.........(3.4)$$

The VA equation (3.3) can also be written as:

$$R - C = NI + LC + I + T + DP.........(3.5)$$

The left hand side of equation (3.5) represents the total value added by the firm and the right hand side explains its distribution to different stakeholders such as wages for employees, interest for creditors, taxes to government and net income for the shareholders and retained earnings.

Step 2

In step two the VAIC is calculated by measuring the human capital (HCE), structural capital (SCE) and capital employed (CEE) efficiencies[19].

$$VAIC = ICE + CEE........(3.6)$$

Where ICE is the intellectual capital efficiency and is expressed as:

[19] The term "Capital Employed Efficiency" is used in the literature as Equity Capital invested by the shareholders.

$$ICE = HCE + SCE........(3.7)$$

HCE measures the ability of the firm to create value through making a one dollar investment in employees and is calculated as:

$$HCE = VA / HC......(3.8)$$

Structural Capital Efficiency (SCE) measures how much capital has been created by structural capital and is calculated as:

$$SCE = SC / VA.......(3.9)$$

Capital employed efficiency measures how much value has been created from each dollar of shareholders' capital and can be calculated as:

$$CEE = VA / CE........(3.10)$$

Hence, VAIC can be written as:

$$VAIC = \frac{VA}{HC} + \frac{SC}{VA} + \frac{VA}{CE} ....(3.11)$$

Variables and proxies:

The variables in equation (3.11) are measured as follows (see Table 3.1 for more details).

- Human capital is measured as the total cost of employees in wages and salaries.
- Capital employed is the book value of total capital employed in the business.
- Structural capital is calculated as SC = VA – HC

3.3 Proposed adjusted-VAIC Model

This section highlights some of the problems, criticisms and solution to the original VAIC model. This current study also uses an adjusted version of VAIC (called A-VIAC) to address some of the problems in the original VAIC model.

3.3.1 Structural Capital Measure

Structural Capital in the VAIC model is the difference between VA and HC, which might be problematic as argued by Ståhle *et al.* (2011). As discussed previously, VA = OP+LC+DP and SC = VA-HC where HC is defined as total cost of employees which is termed the LC (labour cost). Thus, we can say that SC=OP+DP. Ståhle *et al.* (2011) argue that operating profit (OP) and deprecation are perfectly affected by company strategies where the former is affected by present investments and later is affected by the previous year's investments of the company. This calculated parameter is purely an accounting variable comparable to the operating margin of the company and cannot be logically classified as structural capital (Ståhle *et al.*, 2011).

Furthermore, SCE in the VAIC model is calculated as SCE = SC/VA which can be interpreted as: when VA decreases the structural capital, efficiency increases which contradicts financial principles[20]. To solve this problem, following Vishnu and Kumar Gupta (2014), we replace the SC variable with innovation capital (INVC from here onward) for which R&D will be used as a proxy for the following reasons.

Chen *et al.* (2005) argue that traditional accounting standards treat R&D as expenses and are subtracted when calculating VA in VAIC model. Investment in R&D is considered the major driver for technological advancement in innovation, thus these expenses should be treated as an investment. Lev and Sougiannis (1996) and Chauvin and Hirschey (1993) studied the relationship between R&D and advertising investment and future stock performance of the company and report a significant positive relationship. Lev and Sougiannis (1996) regard R&D and advertising investment as the major driver of stock prices whereas Chauvin and Hirschey (1993) conclude that investors expect higher cash flows from R&D and advertising intensive companies. We argue that if personnel cost is treated as investment in the VAIC model then R&D costs should also be treated as an investment since this accumulates structural capital for the firm. Hence we add back R&D investments when calculating VA for our adjusted version of VAIC (A-VAIC)[21]. Following Cheng *et al.* (2008), we use R&D as a proxy for innovation capital so INVC efficiency can be calculated as follows.

$$INVCE = VA / \mathrm{INVC} \ldots\ldots(3.12)$$

Where INVCE measures the ability of the company to create value by making a one dollar investment in innovation capital (*i.e.,* R&D).

Following this change, the adjusted-VAIC model is as follows:

$$A-VAIC = HCE + \mathrm{IN}VCE + CEE \ldots\ldots(3.13)$$

Or

[20] In finance, when VA decreases it means the structural capital has not performed well but, as per the VAIC model, when VA decreases SCE increases, which should not be true.

[21] This is further discussed in Chapter 6.

$$A-VAIC=\frac{VA}{HC}+\frac{VA}{INVC}+\frac{VA}{CE}......(3.14)$$

We use the adjusted version of VAIC model (equation 3.13) to determine if it can solve the existing problems with the original VAIC model.

The independent variables included in this current study are VAIC and its components, HCE, SCE and CEE (right hand side of equation 3.11). When we adjust the original VAIC model, the independent variables become A-VAIC and its components, HCE, INVCE and CEE as in equation (3.13).

Following previous studies (Firer & Williams, 2003; Pal & Soriya, 2012; Joshi *et al.*, 2013), we use firm size as a control variable because it can potentially affect firm performance. Nguyen *et al.* (2015) believe that certain macro-economic variables such as GDP growth might influence firm performance. Moreover, Koller *et al.* (2010) state that a firm's value is directly influenced by future assumptions of macro-economic variables. Therefore, departing from existing studies on IC-firm performance, this current study also applies GDP growth rate as a control variable, we believe that GDP growth rate might influence firm performance, apart from our desired independent variables.

Dependent Variables

This section discusses the dependent variables and their measurement.

3.3.1..1 Profitability measures

Different authors use different profitability measures such as ROA (*Return on Assets*) (Ting & Lean, 2009; Clarke *et al.*, 2011; Hsu & Wang, 2012) and *Return on Equity* (ROE) (Tan *et al.*, 2007; Ståhle *et al.*, 2011; Pal & Soriya, 2012; Kweh *et al.*, 2013; Sumedrea, 2013) to measure the relationship between IC and firm performance. ROA measures the earning capability of a firm by using a dollar of asset and ROE measures the same by using a dollar of equity. In line with the literature, this study uses ROA as the main performance measure with ROE for a robustness check.

$$ROE=\frac{NI}{TE}....(3.15)$$

Where NI is the total net profit left over for the shareholders and TE is total shareholders' equity in the business.

$$ROA=\frac{NI}{TA}....(3.16)$$

Where ROA is return on assets and TA is total assets of the business.

3.3.1..2 *Productivity measure*

Apart from profitability measures, this current study uses other performance measures for robustness purposes. Consistent with (Firer & Williams, 2003; Gan & Saleh, 2008; Pal & Soriya, 2012), we use total *Assets Turnover* (ATO) as a productivity measure which measures the revenue generated from using total assets.

$$ATO = \frac{S}{TA} \text{......(3.17)}$$

Where S is total sales of the firm for the year and TA is total assets held by the firm.

3.3.1..3 *Market measure*

A major objective of an organization is to increase the shareholders' wealth (Ross *et al.*, 2008); there are two ways a company can increase shareholders' wealth. First, a company can distribute its residual profits among the shareholders and second is capital gain, which is preferred, according to Ross *et al.* (2008). Capital gain is the increase in share price in the market over time. In analysing the role of IC in the market value of a firm, this current study employs the M/B ratio for the market value measurement of the company:

$$M / B = \frac{MV}{BV} \text{.....(3.18)}$$

Where MV is market value of the firm calculated by multiplying the number of shares outstanding with market price per share (Ross *et al.*, 2008). BV is book value of equity in the balance sheet of the firm.

3.4 Statistical Models

One of the objectives of this current study is to analyse the impact of IC on the financial performance of the firm to test if the outcomes are in accord with the IC theories discussed in the literature. Since the objective is to explore the relationship between the dependent variable (firm performance, in this case) and independent variables (VAIC and it components), we conduct regression analysis to measure this relationship. This study uses unbalanced panel data as firms (discussed in the next section) have missing values. Following Baltagi (2008) and Gujarati (2012), we begin our analysis with a basic linear regression model (BLRM) and apply OLS to the following models (advanced estimators such as panel data analysis and dynamic panel model are discussed and applied in chapters 4 and 5).

$$FP_{it}(ROA, ROE, \text{ATO}, \text{M/ B}) = \beta_0 + \beta_1 VAIC_{it} + \beta_2 Control + \beta_3 YEAR + \varepsilon_{it} \text{......(3.19)}$$

$$FP_{it}(ROA, ROE, \mathrm{ATO}, \mathrm{M/B}) = \beta_0 + \beta_1 HCE_{it} + \beta_2 CEE_{it} + \beta_3 SCE_{it} + \beta_4 Control$$

$$+\beta_5 YEAR + \varepsilon_{it} \text{.........} (3.20)$$

Equation (3.19) explores the impact of VAIC (collective measure of IC efficiency) on the financial performance of firms. Pulic (2004) and Chen *et al.* (2005) argue that investors may place different values on each component of VAIC, *i.e.,* HCE, SCE and CEE, hence equation (3.20) explores the impact of individual components of the VAIC model on the financial performance of the firms.

Table 3.1 Variables and Measurements

Variables	Measurement
Independent Variables	
HCE (Human Capital Efficiency)	Total salaries and wages
SCE (Structural Capital Efficiency)	VA-HC
CEE (Capital Employed Efficiency)	Total book value of firm
VAIC (Value Added Intellectual Capital Efficiency)	HCE + SCE + CEE
INVCE (Innovation Capital Efficiency)	Total R&D Investment
A-VAIC (Adjusted VAIC)	HCE + INVCE + CEE
Dependent Variables	
ROA (Return on Assets)	Net Income/Total Assets
ROE (Return on Equity)	Net Income/Total Equity
ATO (Assets Turnover)	Total Sales/Total Assets
P/B (Price to Book Ratio)	Market Price/Book Value
Control Variables	
Size	Natural Log of Capitalization
GDP Growth	GDP growth rate
Year	Year dummies

We change the structural capital measurement in the original VAIC model and replace it with R&D as innovation capital in the A-VAIC model. The following equations, (3.21) and (3.22), measure the impact of m-VAIC and its components on the financial performance of firms.

$$FP_{it}(ROA, ROE, \mathrm{ATO}, \mathrm{M/B}) = \beta_0 + \beta_1 A-VAIC_{it} + \beta_2 Control$$
$$+\beta_3 YEAR + \varepsilon_{it} \text{.......} (3.21)$$

$$FP_{it}(ROA, ROE, \mathrm{ATO}, \mathrm{M/B}) = \beta_0 + \beta_1 HCE_{it} + \beta_2 INVCE_{it} + \beta_3 CEE_{it} + \beta_4 Control + \beta_5 YEAR + \varepsilon_{it} \quad \text{.....................} (3.22)$$

Where INVCE is innovation capital efficiency for firm *i* at time *t;* A-VAIC is the adjusted version of VAIC with the inclusion of innovation capital or R&D.

3.5 Sample and Data

This section discusses the sample markets in the study, firms and sources of data used in the study.

3.5.1 Sample Markets and Firms

As discussed in Chapter One, the purpose of this study is to measure IC efficiency and compare it between developed, emerging and frontier countries. The purpose of this comparison is to determine if economic development plays any role in the performance of IC. Previous studies on IC produce quite divergent results. Some studies, Vishnu and Kumar Gupta (2014) and Chen *et al.* (2005) report a significant positive relationship between IC efficiency and firm performance in emerging markets, whereas Firer and Williams (2003) report no relationship. Similarly, Tan *et al.* (2007) report a significant positive relationship between IC and firm performance in developed markets whereas W. H. Su and Wells (2015) and Joshi *et al.* (2013) find no conclusive results in the Australian developed economy. Similar results are documented for the under-developed markets.

These mixed results can be attributed to at least three reasons. First, there is no study in the literature that includes different types of market (developed, emerging and frontier) to look at the bigger picture. There is a gap in the literature whether economic development plays any significant role in the efficiency of IC or if IC can perform efficiently in any given scenario. Second, the existing published studies on IC rely on static measures such as OLS or FE to estimate the relationship between IC and firm performance. In other words, previous studies ignore the dynamic relationship between IC and firm performance (see chapter 4). Third, most studies use the original version of VAIC model, which suffers from criticism of its construction.

To address the first gap in the literature, we expand the study's scope to three types of market, *i.e.*, developed, emerging and frontier markets. As per the MSCI index, countries are divided into three categories, *i.e.,* developed, emerging and frontier countries[22]. Five countries from each region are selected based on their GDP per capita[23]. GPD per capita[24] is applied as the first criterion in sample selection because the IC efficiency is associated with GDP per capita where countries with a good

[22] This list of categories is available from https://www.msci.com/market-cap-weighted-indexes.

[23] Previous researchers who used multiple countries for comparison have resorted to random selection of the countries (Kwan, 2003; De Jong *et al.*, 2008; Young *et al.*, 2009; T. Chen, 2013; Gigante, 2013; Berzkalne & Zelgalve, 2014);

[24] Lists of countries ranked by GDP per capita and KEI are obtained from the World Bank indicators as of 2013.

GDP performance exhibit greater efficiency of IC (Navarro *et al.*, 2011). Cañibano *et al.* (2000) argue that most manufacturing economies are quickly replaced by knowledge-based economies that ultimately increases the importance of IC. We apply the *Knowledge Economy Index* (KEI) as the second criterion in sample selection. KEI scores for each country are from the World Bank development indicators. Countries with higher GDP per capita as well as KEI (see Table 3.2) from each region (developed, emerging and frontier) are selected for the sample. The markets included in our study sample are presented in Table 3.2.

Table 3.2 Sample Markets from Developed, Emerging and Frontier Countries

Developed Markets			**Emerging Markets**			**Frontier Markets**		
Market	**GDP**	**KEI**	**Market**	**GDP**	**KEI**	**Market**	**GDP**	**KEI**
Australia	67.46	8.88	China	6.80	4.37	Argentina	14.76	5.43
Austria	49.05	8.61	Malaysia	10.51	6.10	Nigeria	3.01	2.20
Netherlands	47.61	9.11	Russia	14.61	5.78	Pakistan	1.29	2.45
Singapore	55.18	8.26	South Africa	6.61	5.21	Saudi Arabia	25.85	5.96
Sweden	58.26	9.43	Turkey	10.94	5.16	Ukraine	3.90	5.73

Note: GDP is GDP per capita (amounts are in US$ 000) and KEI is the knowledge economy index. All data are sourced from World Bank Development Indicators 2013.

The next step is to select firms from each market. Firer and Williams (2003) and Zéghal and Maaloul (2010) argue that IC is necessary for firms in every sector hence it should be studied across all sectors. Although IC is important for all types of firm such as small or big, public or private (Kolachi & Shah, 2013), one advantage in selecting publicly listed firms is that data for listed firms are available publicly. Another advantage is that since the annual reports of publicly listed firms are always audited by reliable sources, it increases the reliability of the results (Chen *et al.*, 2005). Based on Kolachi and Shah (2013) argument that IC is important for big firms with as many as 500,000 employees as well as for small firms with 50 employees, we select all publicly listed firms frim in the 15 markets. The study time period is 10 years (2005 to 2014) since Wintoki *et al.* (2012) argue that a panel data study of fewer than 10 years may produce biased results. The time period is specifically chosen to encompass the 2008 global financial crisis that provides a basis to analyse the role of IC in the performance of firms pre and post a financial crisis.

One of the limitations of the VAIC model is that it does not work for the companies with negative value added or losses (Firer & Williams, 2003). Pulic (1998) argues that since firms with negative income do not add any value, their IC efficiencies cannot be calculated. Thus, following previous studies (Shiu, 2006; Ting & Lean, 2009; Zéghal & Maaloul, 2010) we drop from the study firms with negative value added or negative operating profits. Firms in our sample should have at least four years of data; firms with fewer than four years of data were deleted from the sample. There were 11,189 listed firms in the study time period but after carefully reviewing that the firms in the sample met all the above criteria, there were 7,117 listed firms left. Table 3.3 presents the markets list of firms in the sample.

Table 3.3 The Markets List of Firms in the Study Sample

Developed Markets		**Emerging Markets**		**Frontier Markets**	
Market	*Firms*	*Market*	*Firms*	*Market*	*Firms*
Australia	571	China	2536	Argentina	74
Austria	75	Malaysia	874	Nigeria	83
Netherlands	96	Russia	689	Pakistan	215
Singapore	598	South Africa	256	Saudi Arabia	132
Sweden	290	Turkey	280	Ukraine	348

3.5.2 Data sources

This current study uses a monetary measure, *i.e.,* the VAIC model to calculate the IC efficiency, quantitative performance measures such as ROA and ROE, and annual reports data to measure the variables. We obtained firms' financial data from the *Bloomberg* database for the years 2005 to 2014. We also obtain country level data, such as GDP, and other country statistics from the *World Bank development indicators 2013*.

3.5.3 Data Transformation (Natural Logarithm)

The study's scope is expanded over three major markets, *i.e.,* developed, emerging and frontier markets, and covers all publicly listed firms. Therefore, varying size of the firms is expected. Another unique characteristic of the dataset in our study is that it includes more *percentage form* ratio variables such as ROA and ROE as dependent variables and efficiencies such as HCE and SCE as independent variables. Charbaji (2011) argues that ratio variables increase skewness in the data so one should log transform the data for better statistical analysis. Similarly, Osborne (2005) claims that log transformation improves data distribution for statistical testing. The author also argues that all data points remain in the same relative order as they were before transformation. Gujarati (2012) states that log transformation is popular in econometric analysis that measures the rate of change of the slope coefficient (β) *Y* against the *X* variable. However, one precautions is that if there are negative values in the dataset then log transformation might not be useful since a natural log of a negative number is not defined. Since firms with negative operating profits or equity were deleted from our sample, following (Osborne, 2005; Charbaji, 2011; Gujarati, 2012), we take natural logarithms of the variables to increase the efficiency of the econometric analysis.

3.5.4 Data Analysis

We measure the IC efficiency scores for firms in each market with MS Excel and SPSS (version 22) to perform the descriptive analysis. Next we use STATA (version 12) to estimate the static models (OLS & Fixed-Effect) as well dynamic panel data estimator such as system GMM. All diagnostic tests such as unit root, heteroscedasticity and autocorrelation are performed in STATA.

3.6 Chapter Summary

This chapter presents the methodology used in the study. This current study uses the VAIC model to measure IC efficiency. The VAIC and its individual components, HCE, SCE and CEE, are the independent variables. Performance measures, ROA, ROE, ATO and P/B, are the dependent variables in this study. IC measurement models in the literature can be divided into two broad categories, *i.e.*, monetary and non-monetary based measures. Both categories have their pros and cons, e.g., monetary measures provide results in the form of numerical values that are easy to interpret and can be compared across firms and industries (Sydler *et al.*, 2014). Non-monetary measures provide results in the form of indexes that are relatively complex to interpret. Another difference between the two types of measure is that monetary measures rely on financial data from annual reports whereas non-monetary measures use survey data from questionnaires.

One of the most widely used monetary based measure is VAIC model (Pulic, 1998, 2004). The VAIC model measures the value added by the business along with individual contributions of each asset category towards the firm's value creation. Unlike other assessment-based measures that are unable to measure the asset value of IC of a firm, VAIC is an indicator-based measure that uses financial report data and calculates the asset value and efficiency of a firm's IC, which is useful in decision making by management. This current study uses the VAIC model to measure IC efficiency along with its individual components, *i.e.*, human, structural and physical capital. The VAIC model involves a two-step process with value added calculated in the first step and IC efficiency calculated in the second step.

There is criticism of the VAIC model especially on its structural capital measure. We replace the structural capital measure with a new proxy, *i.e.*, R&D, to modify the original VAIC model into the A-VAIC model. In line with the literature, we use ROA as the main performance measure and ROE as the dependent variable for robustness check. This current study also uses a productivity measure, *i.e.,* ATO and a market measure, *i.e.,* M/B, for robustness purposes. This current study also uses firm size and GDP growth rate as control variables since these variables might influence firm performance. The scope of this current study is expanded to three market types, *i.e*., developed, emerging and frontier. GDP and knowledge economy index are the criteria for sample selection. Fifteen countries (five from each market type, see Table 3.2) are in the study to allow comparisons.

Based on the arguments by Firer and Williams (2003) and Kolachi and Shah (2013), this current study includes all publicly listed firms in the selected markets. There were 11189 listed firms in the study time period but after carefully reviewing that firms met the specified criteria, there are 7117 listed firms left in the sample. The data are from the *Bloomberg* database for the period 2005-2014 and country specific data, such as GDP, are from *World Development Indicators* 2013. Following Charbaji (2011)'s argument that ratio based data exhibit problems such as skewness we log transformed the data in the study.

Chapter 4

Static Models (OLS & Fixed-Effects) Results

4.1 Introduction

This chapter reports and discusses the results of static OLS and Fixed-Effects (FE) estimations. The chapter is organised as follows: Section 4.2 discusses the descriptive statistics of the dependent and independent variables. Section 4.3 discusses the diagnostic tests such as multicollinearity and unit root test, and OLS results followed by FE estimations. Section 4.4 presents advanced diagnostic test results such as heteroscedasticity and autocorrelation to check the reliability of the OLS and FE estimates. Section 4.5 explains the problems in the OLS and FE estimates and discusses possible solutions. Section 4.6 summarizes the chapter.

4.2 Descriptive Statistics

One objective of this current study is to measure and compare the IC efficiency and its relationship with the financial performance of firms in different markets. Tables 4.1 to 4.3 report the summary statistics of the dependent and independent variables for developed, emerging and frontier markets, respectively. Table 4.1 shows the mean IC efficiency scores "*measured in terms of VAIC*" vary from 5.08 to 9.28 with an overall mean of 7.90 for the five developed markets in the study. The mean VAIC scores for individual countries are, from lowest to highest, 5.08, 8.01, 8.57, 8.59 and 9.28 for Austria, Netherlands, Sweden, Singapore and Australia, respectively. Among the five developed markets, Australia exhibits the highest and Austria the lowest, which implies that Australian firms use IC more efficiently than the other four developed markets. The mean IC efficiency scores are consistent with those reported by Joshi *et al.* (2013) for Australia (scores 8.82) but the scores are higher than those reported by Chen *et al.* (2005) for Taiwan (5.49). The mean VAIC scores in our study (7.90) are generally higher than for European countries (Czech Republic, Denmark, Finland, Germany, Italy, Norway, Poland, Spain and Sweden) reported by Gigante (2013) and, in particular, the VAIC score for Sweden (8.57) in this current study is much higher than for Sweden (3.97) in that study. These mean IC efficiency scores are slightly lower than those reported by El-Bannany (2008) for UK banks (10.80).

In terms of human capital efficiency, the mean scores vary from 4.13 to 8.06 with an overall mean of 6.66 for the developed markets. Australia again tops the list with Austria at the bottom, which means that firms in Australia use human capital more efficiently than the other four developed markets. The mean HCE score for Australia (8.06) is slightly higher than that reported by Joshi *et al.* (2013) for Australia (7.77).

Table 4.1 Cross-Country Summary Statistics of the Dependent and Independent Variables (Developed Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE	VAIC	GDP	Obs.
Australia	Mean	10.45	21.29	1.06	2.84	8.06	0.54	0.67	9.28	1.30	571
	Median	7.11	14.91	0.85	1.61	1.76	0.49	0.40	2.89	1.73	
	Min	0.27	0.65	0.05	0.25	1.07	0.07	0.02	1.56	-3.79	
	Max	51.06	103.20	4.20	14.06	67.71	1.00	3.95	69.44	3.62	
Austria	Mean	4.66	12.16	0.79	1.64	4.13	0.54	0.43	5.08	2.84	75
	Median	3.74	10.35	0.87	1.24	1.70	0.48	0.33	2.68	2.74	
	Min	0.07	0.38	0.03	0.22	1.11	0.10	0.01	1.71	1.81	
	Max	21.24	43.41	2.04	6.01	22.71	1.00	1.79	23.70	3.75	
Netherlands	Mean	7.68	18.36	1.11	2.29	6.76	0.46	0.64	8.01	0.98	96
	Median	5.84	15.11	1.01	1.81	1.54	0.37	0.50	2.65	1.53	
	Min	0.09	0.35	0.03	0.43	1.05	0.05	0.02	1.79	-3.76	
	Max	32.67	77.32	3.51	9.78	63.29	1.00	3.32	64.56	3.69	
Singapore	Mean	9.80	20.28	1.02	1.83	7.61	0.58	0.39	8.59	5.88	598
	Median	6.73	13.42	0.86	1.03	2.32	0.57	0.26	3.25	5.32	
	Min	0.22	0.43	0.03	0.19	1.15	0.13	0.03	1.59	-0.60	
	Max	49.44	116.26	4.13	12.34	55.08	0.98	1.84	58.01	15.24	
Sweden	Mean	9.34	20.30	1.21	2.95	6.77	0.48	0.98	8.57	1.71	290
	Median	7.06	16.56	1.13	2.09	1.50	0.39	0.53	2.80	2.49	
	Min	0.25	0.60	0.03	0.39	1.03	0.04	0.02	1.65	-5.18	
	Max	41.78	87.86	4.01	14.61	77.90	1.00	6.78	101.34	5.98	
	Overall Mean	8.385	18.479	1.037	2.310	6.664	0.518	0.625	7.905	2.542	

Note: All variables are averaged over 10 years (2005-2014); minimum and maximum values restricted to 1 and 99 percentiles, respectively;. Obs. is number of firms per country in our study.

Source: Author’s calculations

Table 4.2 Cross-Country Summary Statistics of the Dependent and Independent Variables (Emerging Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE	VAIC	GDP	Obs.
China	Mean	7.25	14.57	0.82	3.77	8.19	0.86	0.19	9.18	9.99	2536
	Median	5.21	10.78	0.68	2.70	4.90	0.92	0.13	5.87	9.55	
	Min	0.17	0.45	0.07	0.72	1.43	0.35	0.02	1.95	7.26	
	Max	34.41	62.57	3.06	14.81	54.96	1.00	0.57	57.40	14.19	
Malaysia	Mean	7.26	12.64	0.80	1.39	6.16	0.63	0.24	7.06	4.94	874
	Median	5.31	9.73	0.70	0.86	2.79	0.64	0.20	3.64	5.40	
	Min	0.15	0.29	0.05	0.21	1.22	0.18	0.03	1.69	-1.51	
	Max	32.12	64.61	2.90	9.89	63.64	0.98	0.95	64.65	7.42	
Russia	Mean	7.88	17.48	1.46	1.88	5.08	0.59	0.49	6.15	3.46	689
	Median	4.91	12.00	1.00	1.11	1.74	0.54	0.36	2.82	4.38	
	Min	0.01	0.04	0.06	0.08	1.09	0.09	0.01	1.60	-7.82	
	Max	43.71	109.54	10.04	11.59	22.52	1.00	2.59	24.18	8.53	
South Africa	Mean	10.40	24.08	1.26	2.87	4.52	0.64	0.50	5.10	3.00	256
	Median	8.38	19.43	1.11	1.76	1.90	0.59	0.40	3.07	3.11	
	Min	0.42	0.86	0.05	0.28	1.14	0.13	0.02	1.72	-1.53	
	Max	41.44	108.01	4.96	13.03	48.54	1.00	2.05	46.38	5.58	
Turkey	Mean	8.46	16.43	2.30	2.19	7.07	0.76	0.24	8.02	4.29	280
	Median	5.74	13.07	0.85	1.27	3.06	0.81	0.19	3.99	4.43	
	Min	0.16	0.45	0.04	0.28	1.18	0.17	0.03	1.61	-4.82	
	Max	49.68	74.03	53.63	11.39	88.12	1.00	1.23	89.39	9.15	
	Overall Mean	8.251	17.040	1.327	2.419	6.203	0.697	0.331	7.103	5.136	

Note: All variables are averaged over 10 years (2005-2014); minimum and maximum values restricted to 1 and 99 percentiles, respectively; Obs. is number of firms per country in our study.

Source: Author's calculations

Table 4.3 Cross-Country Summary Statistics of the Dependent and Independent Variables (Frontier Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE	VAIC	GDP	Obs.
Argentina	Mean	7.22	19.89	1.04	1.48	4.11	0.65	0.59	5.39	5.06	74
	Median	5.89	14.47	0.90	1.25	2.35	0.65	0.38	3.54	5.52	
	Min	0.15	0.30	0.08	0.33	1.08	0.08	0.04	1.70	0.05	
	Max	24.08	161.34	3.83	5.50	41.90	1.00	2.27	43.02	9.45	
Nigeria	Mean	3.11	12.13	0.65	1.09	1.49	0.31	6.08	7.82	6.03	83
	Median	1.69	2.91	0.66	0.32	1.46	0.32	5.02	6.66	6.28	
	Min	0.21	1.01	0.17	0.08	1.07	0.07	0.03	2.08	3.44	
	Max	22.64	80.91	0.99	2.85	2.34	1.00	26.31	27.08	8.21	
Pakistan	Mean	9.64	22.56	1.17	2.10	6.40	0.73	0.37	7.54	4.01	215
	Median	7.46	18.52	0.98	1.15	3.58	0.74	0.27	4.64	3.93	
	Min	0.21	0.64	0.08	0.11	1.38	0.28	0.03	1.80	1.60	
	Max	38.49	108.50	4.88	18.74	68.66	1.00	1.70	78.32	7.66	
Saudi Arabia	Mean	9.45	16.60	0.55	3.00	10.35	0.83	0.19	11.36	5.53	132
	Median	7.40	15.12	0.39	2.17	5.12	0.88	0.17	6.17	5.48	
	Min	0.14	0.48	0.02	0.71	1.54	0.37	0.01	2.13	1.82	
	Max	33.59	55.69	2.91	11.95	54.36	1.00	0.66	55.69	9.95	
Ukraine	Mean	6.76	15.71	1.07	28.67	3.11	0.53	0.54	4.21	0.81	348
	Median	2.97	7.72	0.95	1.81	1.91	0.51	0.37	2.98	2.50	
	Min	0.00	0.02	0.00	0.05	1.07	0.07	0.00	1.46	-14.80	
	Max	46.23	96.57	4.21	37.81	17.82	1.00	4.02	20.89	7.90	
	Overall Mean	7.238	17.376	0.896	7.266	5.092	0.610	1.554	7.264	4.288	

Note: All variables are averaged over 10 years (2005-2014); minimum and maximum values restricted to 1 and 99 percentiles, respectively; Obs. is number of firms per country in our study.

Source: Author’s calculations

This minimal difference could be because Joshi *et al.* (2013)'s study includes only Australia financial sector whereas our study includes all listed firms. Nonetheless, this increase in scores after including all firm types shows that IC is necessary for all firms whether in the services sector or manufacturing.

The mean SCE score varies from 0.46 to 0.58 with an overall mean of 0.51 among the five developed markets. Singapore exhibits the highest score (0.58) whereas The Netherlands is the lowest (0.46), which means firms in Singapore accumulate and utilize their structural capital more efficiently than their counterparts in the other four developed markets in this current study. The mean CEE score in the five developed markets varies from 0.39 to 0.98 with an overall mean of 0.62. The mean CEE score for Singapore (0.39) is lowest, which implies that physical capital is no longer a major contributor towards firm value in Singapore.

The mean profitability in terms of ROA varies from 4.66% to 10.45% with an overall mean of 8.38% among the five developed markets (see Table 4.1). The ROE means vary from 12.16% to 21.29% with an overall mean of 18.47%, which is consistent with those reported by Gigante (2013) for most countries such as Denmark (18.58%). Similarly, the mean ATO values vary from 0.79 to 1.21 with an overall mean of 1.03. Among the five developed markets, the mean P/B ratio varies from 1.64 to 2.95 with an overall mean of 2.31. The mean P/B (2.31) is slightly higher than those reported by Chen *et al.* (2005) for Taiwan (P/B 1.95), which means that firms in our sample exhibit a higher P/B ratio.

Table 4.2 reports the descriptive statistics for the five emerging markets. The mean IC efficiency scores vary from 5.10 to 9.18 with an overall mean of 7.10. The mean scores are consistent with those reported by Pek (2005) for Malaysia (7.11) but higher than those reported by Pal and Soriya (2012) for India (4.71 and 4.61 in pharmaceutical and textile industries, respectively). China is top with a 9.18 VAIC score, which means Chinese firms use their intellectual resources more efficiently than their counterparts in other emerging markets. South African firms use IC least efficiently among the emerging markets; this is consistent with Firer and Williams (2003) who conclude that firms in South Africa still focus more on physical capital. The HCE means in emerging markets vary from 4.52 to 8.19 with an overall mean of 6.20. The HCE score for South Africa is the lowest (4.52), which is similar to Firer and Williams (2003) argument that South African firms still rely on physical capital for value creation. The mean structural capital efficiency scores in Table 4.2 vary from 0.59 to 0.86 with an overall mean of 0.69. China tops the list with a mean of 0.86, which means Chinese firms make huge investments in R&D.

The mean profitability in terms of ROA varies from 7.25% to 10.40% with an overall mean of 8.25%, which is slightly lower than that for developed markets (8.38%). The mean ROA for emerging markets is consistent with Pal and Soriya (2012) score for India (8.1%). Similarly, for profitability in terms of ROE, the mean scores vary from 12.64% to 24.8% with an overall mean of 17.4%, which is higher than that reported by Pal and Soriya (2012) for India (13.1%). The mean P/B in the current study is lowest for Malaysia (1.39) and highest for China (3.77) with an overall mean of 2.41 among the five emerging markets. These results are again consistent with Pal and Soriya (2012)'s study which reports a mean M/B ratio of 2.1 for Indian firms.

Table 4.3 reports the descriptive statistics for the five frontier markets in this current study. The mean IC efficiency scores for the frontier markets vary from 4.21 to 11.26 with an overall mean of 7.26. The mean VAIC scores are slightly skewed towards the higher side because Saudi Arabian firms exhibit exceptionally high mean scores (11.26) compared with the other four frontier markets. The mean IC score (7.26) is higher than that reported by Alipour (2012) for Iran (5.8). In terms of human capital, Nigeria scored the lowest (1.49) and Saudi Arabia scored the highest (10.35). The high mean HCE scores for Saudi Arabia contradict Kaplan and Norton (2004)'s argument that countries such as Saudi Arabia and Venezuela are rich in natural resources but make poor investments in their human capital. Our results provide evidence that, in the 21st century, firms rich in natural resources invest in their human resources significantly in order to exploit the knowledge and skill of their employees. The mean SCE scores in frontier markets vary from 0.31 to 0.83 with an overall mean of 0.61. This mean SCE score (0.61) is slightly lower than that reported by Alipour (2012) for Iran (0.83). This difference could be because Alipour (2012)'s study focused only on insurance firms that tend to invest more in human and structural capital to offer new products to their customers. Saudi Arabian firms accumulate and utilize structural capital more efficiently than the other four frontier markets whereas Nigerian firms are least efficient in using structural capital. The mean ROA varies from 3.11% to 9.64% with an overall mean of 7.23%; Pakistani firms achieved the highest profitability rate during one decade. Nigerian firms again performed least efficiently in achieving profitability.

In comparing developed, emerging and frontier markets, the IC efficiency scores are highest for developed markets, which implies that developed countries are most efficient in using IC for value creation. This argument is further supported by the highest mean score for CEE (1.55) in the frontier markets, which implies that firms in frontier markets focus more on financial capital rather than IC. Firms in developed markets exhibit the highest mean ROA (8.38%) followed by emerging markets (8.25%) and is lowest for frontier markets (7.23%). As far macroeconomic variables are concerned, emerging markets exhibit the highest GDP growth rate (5.13%), then frontier markets (4.28%) and is lowest for developed markets (2.54%). This implies that over 2005-2014 emerging markets grew faster than their frontier or developed counterparts.

We also measure the 10 year trend of IC efficiency scores for all three markets. Figures 4.1 and 4.2 present the trends for developed, emerging and frontier markets, respectively. One key point from these figures is that the IC efficiency scores reduced significantly after 2008 for all three types of market (developed, emerging and frontier). One explanation for this downward trend could be the 2008 global financial crisis that may have caused firms to cut back investment in IC. The 2008 global financial crisis affected almost all firms regardless of the size or reputation (Sumedrea, 2013) because the scarcity of funds means cuts in investment are necessary. Nevertheless, the results show that economic development matters in enabling IC resources to contribute towards value creation in firms. This analysis validates the need to expand the scope of IC studies to different regions based upon economic development level, which is the core purpose of this current study.

Figure 4.1 The 10 Year Trends in IC Efficiency Scores Trend for Developed & Emerging Markets

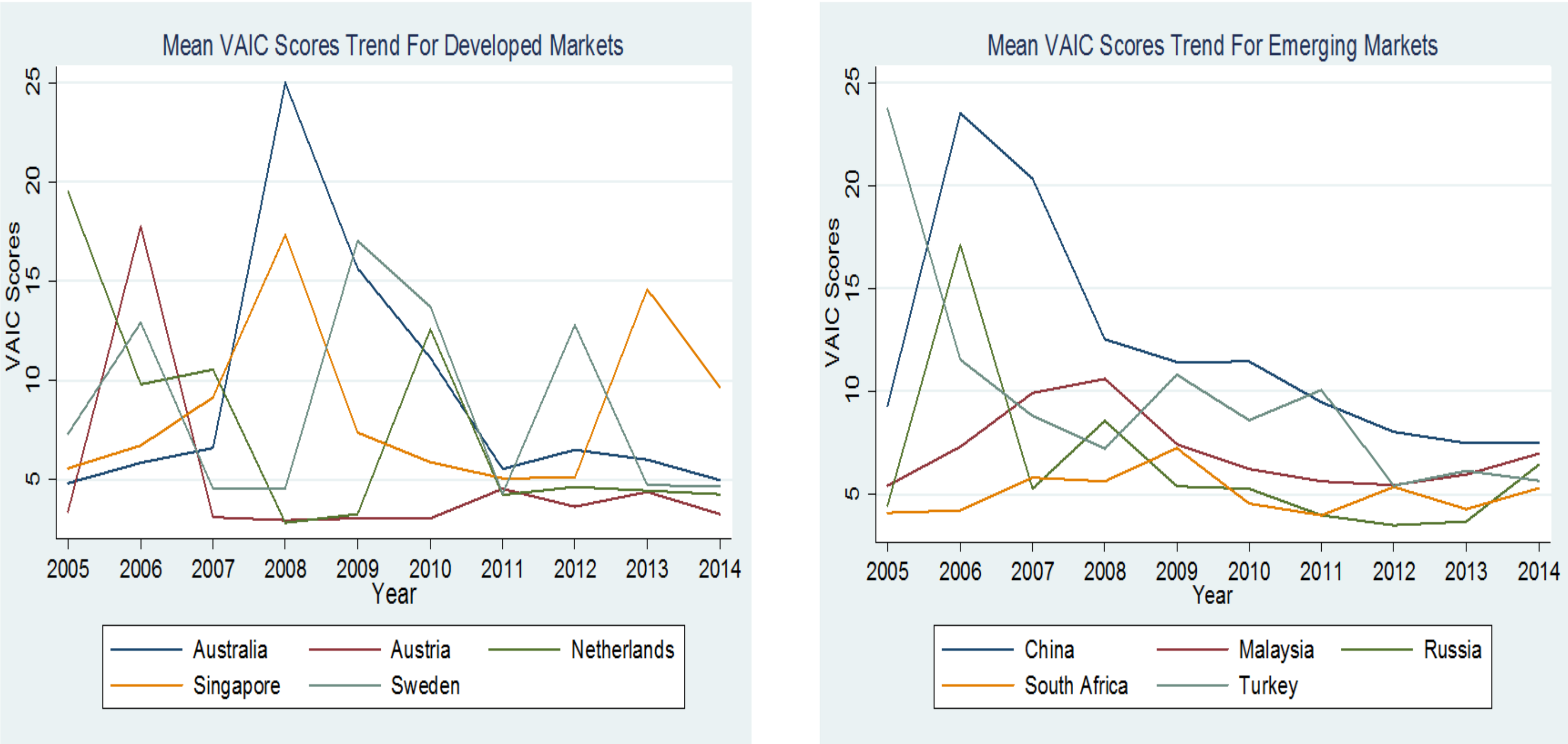
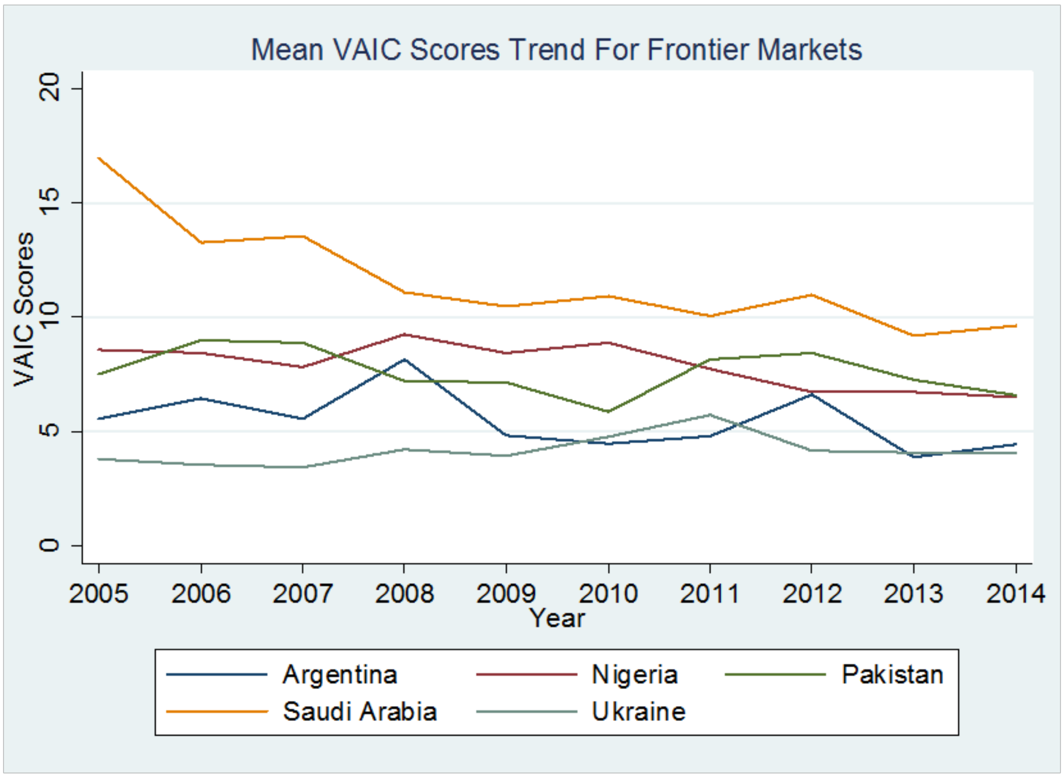


Figure 4.2 The 10 Year Trends in IC Efficiency Scores Trend for Frontier Markets



Source: Author's calculations

4.3 Multiple Regression Results

This section presents the static regression estimation (OLS & Fixed Effect) results used to measure the relationship between IC and firm performance. Following previous studies (Bharathi Kamath, 2008; Clarke *et al.*, 2011; Pal & Soriya, 2012; Joshi *et al.*, 2013; Vishnu & Kumar Gupta, 2014), the analysis begins with OLS followed by fixed effect estimations after applying some basic diagnostic tests. Next we critically analyse the reliability of these estimation techniques along with more advanced diagnostic tests. We systematically analyse what could be possible drawbacks in using static estimation techniques and how previous studies that explored the relationship between IC and firm performance ignored the dynamic nature of this relationship that might produce inconsistent results.

4.3.1 Basic Diagnostic Tests

Before applying the OLS estimator, it is necessary to perform some basis diagnostic tests on the data set. These tests are similar to the several assumptions of Classic Linear Regression Model (CLRM).

4.3.1.1 Unit Root Test

Though it is recent, it has become important to check for the stationarity of panel data (Maddala & Wu, 1999). Testing for stationarity means that the mean and variance of variables does not depend on time. In the field of economics and finance, time related or seasonal shocks in one time period may strongly influence subsequent periods; one basic assumption of CLRM is that current values of variables should be independent of their past values. Gujarati (2012) argues that the application of CLRM to a non-stationary data set can produce spurious results. The author presents an example how the regression of *y* on *x* can produce a statistically significant relationship even though *y* and *x* in reality are not related to each other[25]. This significant relationship (when it should be none) is known as a spurious regression and the results are totally meaningless (Gujarati, 2012). Hence, it is important to check for the stationarity of data before one applies CLRM to those data.

Among the different panel data tests for unit root such as the Lavin-Lin test and the IM-Pesara-Shin test, etc., the only panel data unit root test that incorporates the unbalanced nature of panel data is Fisher-Type *p* test. This test also allows different lag lengths in the individual Augmented Dickey-Fuller test. The test can be written as:

$$P = -2\sum_{i=1}^{n} \ln p_i \rightarrow x^2\left(2n\right) \text{........ (4.1)}$$

Equation (4.1) is designed for relatively smaller N and Choi (2001) presents a modified version of the Fisher-Type test that deals with large N. The test can be written as follows.

$$P_m = \frac{1}{2\sqrt{n}} \sum_{i=1}^{n} \left(-2\ln p_i - 2 \quad\right) \rightarrow N\left(0,1\right) \text{....... (4.2)}$$

This current study applies both the Fisher-Type and Modified Fisher-Type tests to check for stationarity in the unbalanced panel data. The null hypothesis of these tests is that there exists a unit root in the panels. Table 4.4 reports the results of both tests for all 15 markets. Looking at the *p*-values in Table 4.4, the null hypothesis can be rejected at all conventional significance levels in all the countries for all four dependent variables (ROA, ROE, ATO and P/B), which means that there is no unit root in our data. This implies that the means and variances in our data do not depend on time, hence the application of CLRM can produce meaningful results (Gujarati, 2012).

4.3.1.2 Pearson Pairwise Correlation

Another basic assumption of CLRM according to Baltagi (2008) and Gujarati (2012) is that there should be no multicollinearity among the independent variables or regressors. This current study

[25] For an in-depth knowledge, one can read detailed example in Chapter 21 of the basic econometrics book by Gujarati.

applies Pearson pairwise correlation to achieve two objectives. First, to test whether the independent and dependent variables are correlated with each other. The test checks whether there is any correlation between variables or is it worth continuing this study. The second objective is to test the degree of correlation among the regressors. The reason is, if the correlation among the regressors is too strong, say above 0.80, this implies the presence of multicollinearity (Gujarati, 2012), the existence of which violates the basic assumptions of the CLRM as argued by Baltagi (2008). The correlation results are presented in Appendix Tables A1 to A3 for developed, emerging and frontier markets, respectively. The appendices tables show that all independent variables are correlated with the dependent variables in all 15 countries. Appendix Table A1, for example, shows that the IC efficiency in terms of VAIC is positively correlated with firm performance especially in terms of ROA and ROE in all five developed markets. This preliminary evidence endorses the RB theory that IC efficiency increases firm performance in developed markets. Individual components of the VAIC model, HCE, SCE and CEE, are also positively correlated with firm ROA and ROE supporting the RD and OL theories that human, structural and physical capital contribute towards firm performance. The correlation between IC efficiency and other performance measures, *i.e.,* ATO and P/B, however, is quite weak. IC efficiency is also correlated with ROA and ROE in all emerging markets which means that IC also increases firm performance in emerging markets. Similar results are recorded in frontier markets where a correlation is found between IC and firm performance.

The second purpose of correlation analysis is to check for the presence of multicollinearity. The rule of thumb is that the correlation should not exceed 0.80 (Gujarati, 2012). The Appendix Tables A1 to A3 show the correlations between the independent variables do not exceed 0.80 in any specification, which means there is no multicollinearity problem in our data.

4.3.2 Static OLS Estimation Results

The results of the tests (unit root test and multicollinearity) allow the application of OLS estimation between IC and firm performance. Following previous studies (Firer & Williams, 2003; Gan & Saleh, 2008; Ting & Lean, 2009; Clarke *et al.*, 2011; Kai *et al.*, 2011; Pal & Soriya, 2012) we begin with the traditional OLS estimation of our basic regression models.

Tables 4.5 and 4.6 and Appendix Tables B1 and B2 present the results of the OLS estimation for four firm performance measures ROA, ROE, ATO and P/B, respectively (where ROA is our main variable; the rest are used to check for robustness). Model 1 includes VAIC as the independent variable along with control variables and year dummies. Year dummies are included to capture any time related shocks. Model 2 includes the individual components, HCE, SCE and CEE, along with control variables and year dummies. The results in Table 4.5 show IC efficiency is positively significant (at 1%) with firm performance in terms of ROA in all 15 markets.

Table 4.4 The Results of Fisher-Type Unit Root Tests on the Sample Data Set

	ROA		ROE		ATO		P/B	
	Inv. Chi-Sq.	M-Inv. Chi	Inv. Chi-Sq.	M-Inv. Chi	Inv. Chi-Sq.	M-Inv. Chi	Inv. Chi-Sq.	M-Inv. Chi
Developed Markets								
Australia	2470.14*	30.19*	2476.80*	30.91*	2709.66*	35.44*	1952.17*	21.09*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Austria	205.75*	3.49*	22.85*	4.49*	398.76*	14.79*	213.92*	4.26*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Netherlands	335.34*	8.49*	327.52*	8.23*	506.73*	17.62*	379.13*	11.34*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Singapore	2208.41*	23.82*	2063.48*	20.91*	2066.55*	20.85*	2417.80*	33.91*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sweden	1425.72*	27.51*	1368.36*	25.75*	1184.46*	20.10*	813.25*	10.24*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Emerging Markets								
China	1130.00*	72.18*	1110.00*	70.75*	1210.00*	76.54*	1770.00*	147.00*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Malaysia	3003.00*	23.70*	3385.95*	80.00*	3003.00*	23.70*	3385.95*	80.00*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Russia	3771.21*	48.46*	3698.54*	47.64*	3589.74*	44.90*	796.43*	16.50*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	1067.89*	18.76*	1034.89*	18.01*	820.10*	10.97*	915.51*	14.82*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turkey	1228.14*	23.46*	1280.57*	25.25*	963.01*	15.01*	837.06*	13.19*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Frontier Markets								
Argentina	561.69*	25.50*	612.28*	28.87*	782.85*	38.81*	350.93*	15.42*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nigeria	337.46*	11.01*	375.56*	12.62*	267.65*	6.47*	405.50*	14.33*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pakistan	751.18*	12.01*	676.61*	9.59*	701.08*	10.35*	578.16*	6.30*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Saudi Arabia	917.68*	29.04*	888.22*	27.74*	659.18*	17.66*	727.41*	21.88*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ukraine	968.22*	18.46*	1046.45*	22.35*	1290.77*	19.22*	1046.45*	18.46*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: This table presents the t-statistics (p-values in parentheses) of the Fisher-Type original and Modified Unit Root tests; Inv.Chi.Sq. is Inverse Chi-Squired Fisher-Type *P* test and M-Inv.Chi is Modified Inverse Chi-Squired Fisher-Type P_M test; * significance at 0.01.

Source: Author's calculations

These findings support our argument that IC contributes significantly towards firm performance in all types of market. The findings are consistent with previous VAIC studies such as Clarke *et al.* (2011) for Australia, Vishnu and Kumar Gupta (2014) for India, Chen *et al.* (2005) for Taiwan, Ting and Lean (2009) for Malaysia and Rehman *et al.* (2011) for Pakistan. When we conduct individual component analysis in model 2, the results in Table 4.5 show that HCE is not significantly correlated in most markets; the exception is frontier markets. These findings are somewhat contrary to some previous studies (Young *et al.*, 2009; Clarke *et al.*, 2011; Vishnu & Kumar Gupta, 2014) that report a positive, significant relationship between human capital and firm performance. Our findings suggest weak or no relationship in developed and emerging markets. Similarly, some studies (Rehman *et al.*, 2011; Alipour, 2012; Mehralian *et al.*, 2012) find a negative or no relationship between human capital and firm performance in frontier countries whereas our study finds a significant (at 10% or less) positive relationship for Pakistan, Saudi Arabia and Ukraine but a negative significant (at 1%) relationship for Nigeria.

The SCE coefficient in Table 4.5 is significantly, positively correlated with ROA at 1% level in all 15 markets, which implies that firms in developed, emerging and frontier markets realize the importance of structural capital for the innovation in products and services. These results are consistent with Chen *et al.* (2005), Kai *et al.* (2011) and Vishnu and Kumar Gupta (2014) who report a positive, significant relationship between SCE and firm performance in terms of ROA. Contrary to some studies (Firer & Williams, 2003; Ting & Lean, 2009; Clarke *et al.*, 2011), which report a negative relationship between SCE and firm performance, our findings suggest that structural capital contributes positively towards value creation of a firm. The CEE coefficient in Table 4.5 is positive and significantly related to ROA at 1% level in all the markets, which means that firms in developed, emerging and frontier markets rely heavily on financial capital for value creation. These findings are consistent with most IC related studies (Firer & Williams, 2003; Chan, 2009a; Ting & Lean, 2009; Young *et al.*, 2009; Clarke *et al.*, 2011; Joshi *et al.*, 2013; Vishnu & Kumar Gupta, 2014), which report a positive, significant relationship between financial capital and firm performance. The adjusted R^2 varies from 2% to 31% in model 1 and 16% to 58% in model 2, which means that individual component analysis has greater explanatory power.

Table 4.6 reports the results of the relationship between IC and firm performance in terms of ROE for a robustness check. The VAIC coefficient is positive and significant with ROE at 5% level in all 15 markets, which means that IC increases firm performance when measured in terms of ROE. The individual component analysis yields somewhat similar results as ROA. SCE and CEE are again positively and significant (at 5% or less) with ROE in all market types. The HCE coefficient in Table 4.6 produces an inconclusive result, *i.e*., either a negative, weak relationship or no relationship with ROE. This result is consistent with studies (Clarke *et al.*, 2011; Kai *et al.*, 2011; Vishnu & Kumar Gupta,

2014) in which only VAIC and CEE are positive and significantly related to firm performance in terms of ROE. The adjusted R^2 varies from 3% to 19% in model 1 and 22% to 62% in model 2, which is higher than the R^2 in regression with ROA as the dependent variable.

Table 4.5 The Impact of IC on Firm Performance - OLS Results with ROA as the Dependent Variable

	Model 1			Model 2				
	Intercept	VAIC	Adj-R^2	Intercept	HCE	SCE	CEE	Adj-R^2
				Developed Economies				
Australia	1.577*	0.404*	0.08	3.469*	0.029	0.887*	0.789*	0.43
	(0.000)	(0.000)		(0.000)	(0.227)	(0.000)	(0.000)	
Austria	0.724*	0.485*	0.04	3.824*	-0.001	1.558*	0.963*	0.58
	(0.000)	(0.000)		(0.000)	(0.983)	(0.000)	(0.000)	
Netherlands	1.518*	0.246*	0.05	3.723*	-0.025	1.221*	0.950*	0.43
	(0.000)	(0.000)		(0.000)	(0.665)	(0.000)	(0.000)	
Singapore	1.292*	0.425*	0.12	3.270*	0.105*	0.961*	0.706*	0.39
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Sweden	1.483*	0.414*	0.08	3.400*	0.199*	0.972*	0.836*	0.44
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
				Emerging Economies				
China	0.715*	0.263*	0.09	3.250*	-0.002	0.934*	1.057*	0.43
	(0.000)	(0.000)		(0.000)	(0.856)	(0.000)	(0.000)	
Malaysia	0.787*	0.479*	0.09	3.576*	0.023	1.358*	0.855*	0.41
	(0.000)	(0.000)		(0.000)	(0.303)	(0.000)	(0.000)	
Russia	0.250	0.910*	0.11	3.648*	-0.029	1.644*	1.066*	0.36
	(0.107)	(0.000)		(0.000)	(0.570)	(0.000)	(0.000)	
South Africa	1.814*	0.301*	0.09	3.272*	0.010	0.918*	0.559*	0.30
	(0.000)	(0.000)		(0.000)	(0.794)	(0.000)	(0.000)	
Turkey	1.148*	0.463*	0.12	2.499*	0.314*	0.458*	0.484*	0.21
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
				Frontier Economies				
Argentina	0.782*	0.276*	0.02	2.141*	0.022	0.637*	0.485*	0.16
	(0.001)	(0.001)		(0.000)	(0.823)	(0.000)	(0.000)	
Nigeria	-1.194*	0.954*	0.31	1.525*	-1.626*	0.673*	0.430*	0.29
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Pakistan	0.791*	0.614*	0.12	3.484*	0.124*	1.157*	1.085*	0.50
	(0.000)	(0.000)		(0.000)	(0.008)	(0.000)	(0.000)	
Saudi Arabia	1.083*	0.438*	0.15	3.219*	0.216*	0.706*	0.909*	0.54
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Ukraine	0.019	1.026*	0.12	3.191*	0.146***	1.400*	1.010*	0.40
	(0.921)	(0.000)		(0.000)	(0.090)	(0.000)	(0.000)	

Note: This table presents standard coefficients (p-values in parentheses) of OLS results with ROA as the dependent variable; * ** and *** show significance at 0.01, 0.05 and 0.10 level, respectively. Control variables and year dummies were included in every specification.

Source: Author's calculations

Table 4.6 The Impact of IC on Firm Performance - OLS Results with ROE as the Dependent Variable

	Model 1			Model 2				
	Intercept	VAIC	Adj-R^2	Intercept	HCE	SCE	CEE	Adj-R^2
				Developed Economies				
Australia	2.404*	0.367*	0.09	4.111*	-0.006	0.804*	0.657*	0.37
	(0.000)	(0.000)		(0.000)	(0.786)	(0.000)	(0.000)	
Austria	2.467*	0.116	0.03	4.326*	-0.294*	1.041*	0.470*	0.29
	(0.000)	(0.144)		(0.000)	(0.001)	(0.000)	(0.000)	
Netherlands	2.719*	0.146**	0.07	4.363*	-0.161*	0.983*	0.495*	0.29
	(0.000)	(0.010)		(0.000)	(0.005)	(0.000)	(0.000)	
Singapore	2.056*	0.420*	0.12	4.244*	0.032	1.305*	0.729*	0.41
	(0.000)	(0.000)		(0.000)	(0.199)	(0.000)	(0.000)	
Sweden	2.507*	0.367*	0.10	4.267*	0.080*	0.909*	0.648*	0.39
	(0.000)	(0.000)		(0.000)	(0.006)	(0.000)	(0.000)	
				Emerging Economies				
China	1.763*	0.278*	0.15	4.072*	0.034*	0.835*	0.958*	0.50
	(0.000)	(0.000)		(0.000)	(0.004)	(0.000)	(0.000)	
Malaysia	1.367*	0.503*	0.11	4.110*	0.041***	1.366*	0.817*	0.44
	(0.000)	(0.000)		(0.000)	(0.050)	(0.000)	(0.000)	
Russia	1.337*	0.871*	0.11	4.840*	-0.173*	1.773*	0.986*	0.40
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
South Africa	2.701*	0.322*	0.12	4.309*	-0.032	1.028*	0.545*	0.38
	(0.000)	(0.000)		(0.000)	(0.347)	(0.000)	(0.000)	
Turkey	2.085*	0.318*	0.07	3.621*	0.093**	0.719*	0.476*	0.22
	(0.000)	(0.000)		(0.000)	(0.022)	(0.000)	(0.000)	
				Frontier Economies				
Argentina	1.476*	0.412*	0.06	3.265*	0.120	0.584*	0.734*	0.30
	(0.000)	(0.000)		(0.000)	(0.208)	(0.000)	(0.000)	
Nigeria	2.771*	-0.727*	0.19	3.573*	-1.640*	0.655*	-0.498*	0.41
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Pakistan	2.142*	0.470*	0.12	4.435*	0.004	1.243*	0.794*	0.47
	(0.000)	(0.000)		(0.000)	(0.914)	(0.000)	(0.000)	
Saudi Arabia	2.114*	0.282*	0.08	4.730*	-0.047	1.362*	0.929*	0.62
	(0.000)	(0.000)		(0.000)	(0.159)	(0.000)	(0.000)	
Ukraine	0.805*	1.048*	0.14	4.047*	0.084	1.418*	0.989*	0.44
	(0.000)	(0.000)		(0.000)	(0.259)	(0.000)	(0.000)	

Note: This table presents standard coefficients (p-values in parentheses) of OLS results with ROE as dependent variable; * ** and *** show significance at 0.01, 0.05 and 0.10 level, respectively. Control variables and year dummies were included in every specification.

Source: Author’s calculations

We also conducted regression analysis with two more firm performance measures (ATO & P/B) for a robustness check. Appendix Tables B1 and B2 give the results of the relationship between IC and ATO and P/B, respectively. Appendix Table B1 shows that IC efficiency is negative and significantly related (at the 10% level) to firm performance in terms of ATO. Similarly, IC is negatively related to P/B (see Appendix Table B2) but is statistically insignificant. The individual component analysis produces similar results where HCE and SCE are negative and significantly related to ATO at the 10% level (see Appendix Table B1) for most markets. CEE, however, yields mixed results. This is not a surprise since these results are consistent with previous studies (Firer & Williams, 2003; Kai *et al.*, 2011; Mehralian *et al.*, 2012; Gigante, 2013) that also report that IC is significantly related to firm performance when measured in terms of ROA and ROE but weakly or not related to firm performance when measured in terms of either ATO or the P/B ratio.

Most IC studies (Bharathi Kamath, 2008; Kamal *et al.*, 2012; Gigante, 2013; Vishnu & Kumar Gupta, 2014) rely on OLS estimation but there are several underlying assumptions of OLS that must be checked for the robustness of the results (Baltagi, 2008; Gujarati, 2012). According to Gujarati (2012), the OLS model is likely to produce highly significant results and a higher R^2 as it does in this study. One major problem is that OLS does not distinguish between cross sections, *i.e.,* firms in our case. In other words, OLS does not depict whether the response of firm performance to VAIC, HCE, SCE and CEE is similar or different over time and among cross-sections. If the response over time is different then the CLRM suffers from a heterogeneity problem.

The heterogeneity problem can, however, be eliminated through the FE model because it allows individuals to have their own different intercepts. In other words, one can control for firm specific fixed effects in FE regression, which is not possible in OLS. The next section reports and discusses the FE estimation of our basic regression models.

4.3.3 Fixed-Effects Estimation Results

Baltagi (2008) argues that fixed-effects controls for the individual effects hence overcomes the problem of OLS estimation where individual specific effects are dumped into the error term. In this section, we apply the FE estimator to measure the impact of IC efficiency on the financial performance of firms in developed, emerging and frontier markets. Table 4.7 and Appendix Tables C1 to C3 present the results of the fixed-effects estimations with ROA, ROE, ATO and M/B as the dependent variables, respectively. The FE estimation results are quite similar to those obtained by the OLS estimation. Table 4.7 shows the VAIC coefficient is positive and significantly related to firm performance (ROA) at the 1% level in almost all markets; the exception is the Netherlands. These results are consistent with previous IC related studies (Ting & Lean, 2009; Young *et al.*, 2009; Rehman *et al.*, 2011; Alipour, 2012; Vishnu & Kumar Gupta, 2014) that also report a significant, positive relationship between VAIC and firm performance in developed markets such as Australia, emerging markets such as Malaysia and China and frontier markets such as Iran and Pakistan.

Table 4.7 The Impact of IC on Firm Performance: Fixed Effects Results with ROA as the Dependent Variable

	Model 1			Model 2				
	Intercept	VAIC	R^2	Intercept	HCE	SCE	CEE	R^2
				Developed Economies				
Australia	1.247*	0.708*	0.09	3.353*	0.116*	0.895*	0.667*	0.42
	(0.000)	(0.000)		(0.000)	(0.003)	(0.000)	(0.000)	
Austria	1.027*	0.284*	0.04	3.674*	-0.173***	1.498*	0.713*	0.57
	(0.000)	(0.003)		(0.000)	(0.075)	(0.000)	(0.000)	
Netherlands	1.754*	0.083	0.05	3.539*	-0.148**	1.199*	0.537*	0.35
	(0.000)	(0.176)		(0.000)	(0.013)	(0.000)	(0.000)	
Singapore	1.072*	0.662*	0.12	3.497*	0.062**	1.143*	0.710*	0.39
	(0.000)	(0.000)		(0.000)	(0.043)	(0.000)	(0.000)	
Sweden	1.456*	0.516*	0.09	4.079*	-0.079	1.387*	0.825*	0.40
	(0.000)	(0.000)		(0.000)	(0.176)	(0.000)	(0.000)	
				Emerging Economies				
China	0.606*	0.541*	0.08	2.953*	0.146*	0.739*	0.813*	0.40
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Malaysia	0.757*	0.557*	0.09	3.649*	0.035	1.243*	0.922*	0.41
	(0.000)	(0.000)		(0.000)	(0.151)	(0.000)	(0.000)	
Russia	0.223***	1.067*	0.11	3.226*	0.082	1.389*	0.835*	0.36
	(0.074)	(0.000)		(0.000)	(0.204)	(0.000)	(0.000)	
South Africa	1.852*	0.299*	0.10	3.669*	-0.088**	1.201*	0.646*	0.31
	(0.000)	(0.000)		(0.000)	(0.039)	(0.000)	(0.000)	
Turkey	1.373*	0.302*	0.12	2.650*	0.099***	0.374*	0.449*	0.19
	(0.000)	(0.000)		(0.000)	(0.077)	(0.005)	(0.000)	
				Frontier Economies				
Argentina	0.506**	0.476*	0.04	2.282*	-0.019	0.994*	0.447*	0.17
	(0.018)	(0.000)		(0.000)	(0.866)	(0.000)	(0.000)	
Nigeria	-0.028	0.236*	0.19	0.709***	-0.883**	0.086	0.106**	0.19
	(0.883)	(0.005)		(0.086)	(0.026)	(0.670)	(0.013)	
Pakistan	0.737*	0.691*	0.13	3.442*	0.078	1.085*	0.997*	0.51
	(0.000)	(0.000)		(0.000)	(0.165)	(0.000)	(0.000)	
Saudi Arabia	0.218	0.892*	0.16	3.767*	0.090	1.699*	0.859*	0.52
	(0.149)	(0.000)		(0.000)	(0.176)	(0.000)	(0.000)	
Ukraine	-0.213	0.994*	0.12	2.864*	0.111	1.486*	0.720*	0.39
	(0.176)	(0.000)		(0.000)	(0.253)	(0.000)	(0.000)	

Note: This table presents results from the fixed-effects estimation with ROA as the dependent variable; *, ** and *** represent significance at 0.01, 0.05 and 0.10, respectively. Control variables and year dummies were included in every specification;

Source: Author's calculations

The results in Table 4.7 show that SCE and CEE are significant at 5% level in almost all markets but HCE is negative and insignificant. This means that firms treat salaries and wages as expenditure rather than investment as stated in the RBV theory. Appendix C1 reports the results of the fixed-effects with ROE as the dependent variable where the VAIC, SCE and CEE coefficients are positive and significant at the 10% level in almost all markets (developed, emerging and frontier). This implies that IC significantly contributes towards value creation of firms. Appendix Tables C2 and C3 produce inconclusive results especially for individual component analysis, *i.e.,* weak or no relationship between HCE and firm performance in terms of ATO and P/B, respectively. However, VAIC is still positive and significant at 10% level (Appendix Tables C2 and C3).

4.4 Advanced Diagnostic Tests

One important assumption of CLRM is that the error term is constant over time as well as across cross sections; violation of this could cause heteroscedasticity (Gujarati, 2012). Similarly, the error term should not be correlated with its past values; violation of this assumption means that there is serial correlation in the data and OLS or fixed-effects estimation will no longer be the *Best Linear Unbiased Estimator* (BLUE). In the next sections, we investigate these two assumptions of CLRM.

4.4.1 Breusch-Pagan / Cook-Weisberg Test for Heteroscedasticity

assumption of CLRM is that the variance of the error term is constant over time and individuals or disturbances are homoscedastic (Baltagi, 2008). In other words, the error term μ_i is equal to a constant number, which is $\sigma^{2,}$ and numerically can be written as:

$$E\,(\mu^2_i\,) = \sigma^2 \text{ where } i = 1, 2, \ldots.n \ldots(4.3)$$

This assumption is, however, very restrictive especially for panel data where cross sections (firms in our case) may be of varying size, which can easily lead to violation of this assumption. There could be many sources of heteroscedasticity including changing habits of people, the presence of extreme values (outliers) in the data, adding too many or too few variables (Gujarati, 2012). One potential source of heteroscedasticity in our data could be the different sizes of firms (small versus big), which prompts the need to test for heteroscedasticity. We use the Breusch-Pagan Test since it can overcome the limitation of correctly identifying the X variables that is not in possible with the Goldfeld-Quandt Test. The Breusch-Pagan Test can be illustrated in simple numerical equations as follows.

We assume our basic model where firm performance (FP) depends on X variables:

$$FP_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots\ldots\ldots + \beta_k X_{ki} + u_i \quad \ldots..(4.4)$$

and that the error term σ^2 is:

$$\sigma^2 = f(\alpha_1 + \alpha_2 Z_2 + \ldots\ldots \alpha_k Z_{ki}) \ldots. \text{ (4.5)}$$

Equation 4.5 assumes that σ^2 is a linear function of Z variables or $\alpha_2 = \alpha_3 = 0$ or $\sigma^2_i = \alpha_1$ which is constant. We test the null hypothesis of the Breusch-Pagan Test that $\alpha_2 = \alpha_3 = 0$, which is so for homoscedasticity.

Table 4.8 presents the results of Breusch-Pagan Test for models 1 and 2 with four dependent variables (ROA, ROE, ATO and P/B) for all 15 markets. From the *p-values* in Table 4.8, the null hypothesis can be rejected in all 15 markets with all four performance measures, which means that the error variance is not constant or there is heteroscedasticity in the data. Baltagi (2008) and Gujarati (2012) argue that the OLS estimation in the presence of heteroscedasticity could still be consistent but is no longer efficient. The basic assumption of the CLRM is that β_2 is BLUE. So, even if the estimation in the presence of heteroscedasticity is linear, unbiased and consistent but not BLUE these estimations are not efficient since the variance is not minimum.

Table 4.8 The Results of the Breusch-Pagan / Cook-Weisberg Test for Heteroscedasticity

	ROA		ROE		ATO		P/B	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Developed Markets								
Australia	44.04*	433.93*	96.21*	633.03*	15.63	247.06*	133.67*	24.81*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.110)	(0.000)	(0.000)	(0.015)
Austria	26.11*	116.43*	31.02*	79.49*	18.92**	168.49*	7.97	92.02*
	(0.003)	(0.000)	(0.000)	(0.000)	(0.041)	(0.000)	(0.631)	(0.000)
Netherlands	15.27	65.55*	44.59*	75.47*	24.16*	123.43*	25.51*	33.92*
	(0.122)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.004)	(0.000)
Singapore	60.87*	745.44*	70.74*	695.04*	100.51*	583.97*	70.25*	216.09*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sweden	74.96*	284.40*	97.48*	577.20*	63.20*	189.92*	57.53*	30.15*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Emerging Markets								
China	76.95*	1194.6*	61.51*	2397.3*	265.14*	1206.6*	147.09*	412.05*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Malaysia	23.32*	1603.0*	41.16*	2026.2*	144.74*	344.70*	394.62*	234.31*
	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Russia	83.90*	330.99*	159.97*	795.39*	75.13*	84.64*	15.31	24.16*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.121)	(0.019)
South Africa	54.33*	483.46*	69.78*	800.17*	7.47	68.80*	41.09*	85.51*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.680)	(0.000)	(0.000)	(0.000)
Turkey	13.00	111.09*	38.82*	212.08*	32.83*	281.12*	63.50*	124.10*
	(0.223)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Frontier Markets								
Argentina	26.45*	50.07*	33.22*	145.42*	8.93	58.47*	56.70*	104.62*
	(0.003)	(0.000)	(0.000)	(0.000)	(0.538)	(0.000)	(0.000)	(0.000)
Nigeria	9.24	10.90	282.26*	316.91*	417.58*	623.36*	340.46*	382.20*
	(0.509)	(0.537)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pakistan	40.90*	287.76*	51.63*	362.80*	27.64*	53.37*	78.59*	167.79*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Saudi Arabia	60.19*	350.38*	108.42*	569.77*	55.00*	78.84*	11.68	34.87*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.307)	(0.000)
Ukraine	157.03*	250.77*	211.88*	435.44*	79.27*	301.90*	65.81*	78.68*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: This table presents Chi2 (*p-values* in parentheses) of the Breusch-Pagan Test for heteroscedasticity; model 1 includes VAIC and model 2 includes VAIC and HCE, SCE, CEE as independent variables;. Superscripted *** and **** show significance at 0.01and 0.05, respectively.

Source: Author's calculations

4.4.2 Autocorrelation Test

The CLRM assumes that there is no autocorrelation in the disturbance term. In other words, the error term relating to one particular observation is not influenced by the error term of the other observation. This relationship can be written symbolically as:

$$cov(u_i, u_j | x_i, x_j) = E(u_i\, u_j) = 0 \quad \text{where } i \neq j \text{..... (4.6)}$$

Baltagi (2008) and Gujarati (2012), however, argue that this assumption might be very restrictive in cross-section data especially in economics and finance where shocks in the current period might influence coming periods. The point of concern is: "What happens to CLRM if the disturbance terms are correlated? Baltagi (2008) argues that the estimation of the linear panel model in the presence of autocorrelation is consistent but inefficient because of downward biased standard errors. Autocorrelation in panel data can be detected using several tests such as the Baltagi-Wu test, Durbin-Watson test and the Breusch-Godfrey test. According to Drukker (2003), these tests employ many specification assumptions such as individual effects types, need for non-stochastic regressors and inability to work in the presence of heteroscedasticity. Drukker (2003) further argues that the autocorrelation test of Wooldridge (2002) does not have such limitations and can also deal with unbalanced panel data with and without gaps in the observations. Therefore, this test fits in our study and can be written as:

$$y_{it} - y_{it-1} = (\mathrm{X}_{\mathrm{it}} - \mathrm{X}_{\mathrm{it-1}})\beta_1 + e_{it} - e_{it-1} \text{..... (4.7)}$$

or

$$\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta e_{it} \text{..... (4.8)}$$

Where y_{it} is firm performance (ROA, ROE, ATO and P/B), X_{it} is a vector of independent variables such as VAIC, HCE, SCE and CEE, and e_{it} is the error term. This test uses the residuals from the simple regression in the first difference Δ and test the null hypothesis that there is no autocorrelation. We estimate this test with the user written command "*xtserial*" in STATA (version 12), which implements the Woolridge test for serial correlation in unbalanced panel data. Appendix Table D reports the results of the Woolridge (2002) autocorrelation test for all 15 markets with four dependent variables. By the *p-values* in Appendix Table D, the null hypothesis can be rejected at the 5% significance level, which means that there is autocorrelation in the data.

4.5 Reliability of Static Models (OLS &FE) and Possible Solutions

The diagnostic tests (heteroscedasticity and autocorrelation) reject the null hypotheses that there is heteroscedasticity as well as autocorrelation in the data. The question is how reliable are the estimates from OLS and FE? What are the possible solutions to these problems? As argued by Baltagi (2008), the estimations of OLS are consistent but inefficient in the presence of heteroscedasticity and autocorrelation as the standard errors are downward biased and CLRM assumes that the disturbance terms are constant and independent across cross-sections and time. Similarly, FE estimation also assumes that the disturbance term v_{it} is identically distributed and independent of v_{it} for all i and t. Since our estimates (OLS & FE) are inefficient, we now try to find solutions to these problems.

One prominent solution to heteroscedasticity suggested by Gujarati (2012) is to assign weights to each observation in the data. He argues that observations from a population with less variability should carry more weight and those coming from a population with greater variability should have less weight in the regression. In other words, the weights should be inversely related to the standard deviation of the observations. Simple OLS and FE cannot incorporate these weight phenomena but this problem, however, can be overcome by running Generalized Least Squares (GLS), which assigns weights to each observation and solves the problem of heteroscedasticity. Similarly, the problem of autocorrelation, according to Baltagi (2008) and Gujarati (2012), can be solved in few ways such as adding more independent variables, data transformation such as taking logarithms and using lags of dependent variable as regressors.

However, we suspect another missing link between IC and firm performance. This missing link is the potential existence of an *endogeneity* problem that is mainly because of *simultaneity* or reverse causality in the IC - firm performance relationship. In the literature, the focus has been on a one way relationship, *i.e.*, how does IC efficiency affect the financial performance of the firm? But there is a possibility that IC efficiency is also being affected by past firm performance, which is the case with simultaneity. If simultaneity exists (a cause of endogeneity), then the usual static models such as OLS and FE (this issue is further discussed in chapter 5) do not generate BLUE estimations (Wintoki *et al.*, 2012) rather, the Dynamic Panel Data (DPD) estimator should be used (Gujarati, 2012). However, no existing study in the literature has explored the dynamic nature of the relationship between IC and firm performance.

In the next chapter, we test whether the relationship between IC and firm performance is dynamic and how this relationship should exactly be estimated.

4.6 Chapter Summary

This chapter reports the results of descriptive statistics, static OLS and Fixed-Effects (FE) estimation models. Mean IC efficiency scores "*measured in terms of VAIC*" vary from 5.08 to 9.28 with an overall mean of 7.90 for all five developed markets in this current study. Among the five developed markets, Australia scores highest and Austria lowest, which implies that Australian firms use IC more efficiently than the other four developed markets. The mean IC efficiency scores are consistent with those reported by Joshi *et al.* (2013) for the Australian financial sector (8.82), however, the scores are higher than those reported by Chen *et al.* (2005) for Taiwan (5.49). In terms of human capital efficiency in developed markets, the mean scores vary from 4.13 to 8.06 with an overall mean of 6.66. Australia once again tops the list with Austria at the bottom, which means firms in Australia use human capital more efficiently than the other four developed markets. The SCE scores vary from 0.46 to 0.58 with an overall mean of 0.51 among the five developed markets. The CEE scores among the five developed markets vary from 0.39 to 0.98 with an overall mean of 0.62. The mean CEE scores for Singapore (0.39) are lowest, which implies that physical capital is no longer considered a major contributor towards firm value in Singapore.

Among emerging markets, the mean IC efficiency scores vary from 5.10 to 9.18 with an overall mean of 7.10. The mean scores are consistent with those reported by Pek (2005) for Malaysia (7.11) but higher than those reported by Pal and Soriya (2012) for India. The mean HCE scores in emerging markets vary from 4.52 to 8.19 with an overall mean of 6.20. The HCE for South Africa is lowest (4.52), which is similar to Firer and Williams (2003)'s argument that South African firms still rely on physical capital for value creation. Among the emerging markets, the structural capital scores in Table 4.2 vary from 0.59 to 0.86 with an overall mean of 0.69.

The IC efficiency scores for frontier markets vary from 4.21 to 11.26 with an overall mean of 7.26. The mean VAIC scores are slightly skewed towards the higher side because Saudi Arabia exhibited exceptionally high scores (11.26) compared with the other four frontier markets. In terms of human capital, Nigeria scored the lowest (1.49) and Saudi Arabia the highest (10.35). These high HCE scores contradict Kaplan and Norton (2004)'s argument that countries such as Saudi Arabia and Venezuela are rich in natural resources but make poor investment in their human capital. Our results provide evidence that in the 21st century firms rich in natural resources are significantly investing in their human resources. In terms of the developed, emerging and frontier markets, the IC efficiency scores are highest in developed markets, which means that developed countries are most efficient in using IC for value creation.

This current study applies both Fisher-Type and Modified Fisher-Type tests to check for stationarity on the unbalanced panel data. From *p*-values in Table 4.4 the null hypothesis can be rejected at all conventional significance levels in all the countries for all four dependent variables (ROA, ROE, ATO and P/B), which means that there is no unit root in our data. Pearson pairwise correlation results show that correlations among the regressors do not exceed 0.80, which implies that there are no issues of multicollinearity. The OLS results show that IC efficiency in terms of VAIC is positive and significant at 1% with ROA in all 15 markets in this study. This shows that IC resources contribute significantly towards value creation of firms, which endorses the RB theory. Individual components of the VAIC model show that only SCE and CEE are significant (at 10% or less) with ROA in most markets whereas HCE is either negative or insignificant in nine markets in the study. Our robustness checks indicate that IC is significant only with ROE but insignificant with ATO and the P/B ratio.

Fixed-effects analysis of the relationship between IC and firm performance shows that VAIC is positive and significant (at 5% or less) in all developed, emerging and frontier markets. Individual component analysis produces similar results to OLS. HCE is once again negative or insignificant with ROA whereas SCE and CEE are significant (at 5% or less) in almost all markets. Advanced diagnostic tests, such as the Bruesch-Pagan test for heteroscedasticity and Wooldridge test for autocorrelation, reject the null hypotheses which means that there is heteroscedasticity and autocorrelation in the data.

As argued by Baltagi (2008), the estimations of OLS are consistent but inefficient in the presence of heteroscedasticity and autocorrelation as the standard errors are downward biased and CLRM assumes that the disturbance terms are constant and independent across cross-sections and time. Similarly, FE estimator also assumes that the disturbance term v_{it} is identically distributed and independent of v_{it} for all i and t. These problems can be solved in many ways such as through the application of GLS, taking first difference or data transformation. However, we suspect another econometric problem, *i.e.*, the presence of endogeneity. The literature has so far considered the IC and firm performance relationship as one way but we look at it from another angle, *i.e.,* firm performance might also affect IC and this is simultaneity. As argued by Gujarati (2012), the application of OLS or FE produces biased, inconsistent results in the presence of endogeneity (mainly because of simultaneity). In the next chapter, we test whether the relationship between IC and firm performance is dynamic and how this relationship should exactly be measured.

Chapter 5

Dynamic Panel Data Estimation Results

5.1 Introduction

This chapter discusses the dynamic nature of the relationship between IC and firm performance. Section 5.1 discusses the theoretical and empirical evidence of the dynamic relationship and section 5.2 explains how the application of static OLS and fixed effects estimators can produce biased and inconsistent results. Section 5.3 identifies how many lags of firm performance are significant and should be included in the dynamic estimation. Section 5.4 discusses the results and justification of GMM estimator for the study. Section 5.5 discusses the diagnostic tests of the System GMM estimator. Section 5.6 explores the relationship between IC and firm performance during the 2008 financial crisis and section 5.7 concludes this chapter.

5.2 The Dynamic Relationship between IC and Firm Performance

This section discusses the nature of the relationship between IC and firm performance. First, we provide theoretical justification from the literature that forms the basis of our argument, *i.e.,* the relationship between IC and firm performance is dynamic. Next we provide some empirical evidence to support the argument.

5.2.1 Theoretical Evidence

The literature on IC and firm performance focuses on one direction, *i.e.,* IC efficiency affects the financial performance of firms. There is a missing link in the literature, *i.e.,* whether firms' past performance affects the efficiency of IC. Most literature on IC (Sveiby, 1997; Pulic, 1998; Bontis, 2001; Pulic, 2004; Subramaniam & Youndt, 2005) agrees at least on three components of IC namely, human capital, structural capital and relational capital. Each of these components requires appropriate investment to accumulate IC resources (Rastogi, 2003). Firms' investment in these resources is objective driven and is made to achieve specific goals. For example, a firm will invest in human capital to increase employees' motivation level or to enable its employees to generate new ideas. Similarly, investment in R&D (also known as structural capital in the literature) is made to bring innovation to existing products or to bring new products to the market. According to the pecking order theory (Myers & Majluf, 1984), firms follow a particular order while generating their funds. The authors argue that firms use internally generated funds as the first priority before taking loans or raising new equity. In general, the main source of internally generated funds is firms' profits (Ross *et al.*, 2008).

The above argument postulates that firms' investments depend on their profit levels if they follow the pecking order theory. It is quite common that firms invest (in the forms of salary increments or bonuses) in their employees when profits increase. Similarly, for R&D, firms make more investments when they observe higher profits or growth in their cash flows (Mulkay *et al.*, 2001; Becker, 2013). Brown *et al.* (2009) in their study about R&D expenditure in mature high-tech firms in US find that cash flows correlate positively and significantly with investment in R&D. Harmantzis and Tanguturi (2005) in their study on the determinants of R&D expenditure in US telecommunication firms find that a firm's last year performance, in terms of market value and revenue, significantly affects the current year's investment in R&D. This evidence suggests that the relationship between the IC components and a firm's performance is not unidirectional but bidirectional, which means that lagged firm performance also affects current or future year IC efficiency. This argument is consistent with Murthy and Mouritsen (2011) view that a firm's financial performance is the basis for determining investment in IC resources.

If the relationship between IC and firm performance is two-way[26] (also known as simultaneity), then according to Baltagi (2008) and Gujarati (2012), the application of static estimators such as OLS or FE will lead to biased results because of simultaneity (a cause of endogeneity). There is no evidence in in the literature that this issue has been explored. The next section empirically analyses the nature of this relationship.

5.2.2 Empirical Evidence

Gujarati (2012) states that one method to investigate if the empirical model is dynamic or static is to test whether the lagged dependent variable is also a regressor. If the test is significant, then it implies that the model is dynamic and should be estimated with dynamic panel data models. Given this argument, our basic linear model can be written as a dynamic model with the lagged dependent variable as:

$$FP_{it} = \alpha + FP_{it-1} + \Omega\beta_1 X_{it} + \partial\beta_2 Z_{it} + \eta_i + e_{it} \text{ .... (5.1)}$$

where *FP* is firm performance and FP_{it-1} is lagged firm performance, *X* is vector of IC capital components, ∂ is a vector of control variables, η_i is unobserved firm specific effect and e is error term for firm *i* at time *t*.

[26] This means it's not only IC that affects firm performance but firm performance also has a significant influence on IC efficiency.

5.1.2.1 Dynamic OLS Estimation (between IC and Firm Performance)

Following Wintoki *et al.* (2012), we apply dynamic OLS to equation (5.1) to test if the coefficient of the lagged dependent variable is significant. Table 5.1 presents the results of dynamic OLS estimations with ROA as the dependent variable. The first clear indication according to Wintoki *et al.* (2012) is the change in adjusted $R^{2,}$ *i.e.,* if there is any increase in the adjusted R^2 from static OLS to dynamic OLS. Table 5.1 shows the adjusted R^2 increases significantly from static to dynamic OLS. The average increase in adjusted R^2 in developed markets is 43% in model 1 (where VAIC is the independent variable) and 16% in model 2 (where HCE, SCE and CEE are the independent variables). Similarly, the average increase in adjusted R^2 in emerging markets is 42% in model 1 and 25% in model 2. Frontier markets exhibit an average increase in adjusted R^2 of 49% in model 1 and 31% in model 2. This increase in adjusted R^2 from static OLS to dynamic OLS is a clear indication that the IC and firm performance relationship is dynamic. Apart from the increase in adjusted R^2, the coefficients of the lagged dependent variables in models 1 and 2 are statistically significant at 0.01 level in all 15 markets. This further strengthens our argument that this relationship is dynamic.

Table 5.1 The Dynamic OLS Results with ROA as the Dependent Variable (the Impact of IC on Firm Performance)

	Model 1 (VAIC)			Model 2 (HCE, SCE, CEE)				
	Lag-DV	VAIC	Adj-R^2 (ΔAdj-R^2)	Lag-DV	HCE	SCE	CEE	Adj-R^2 (ΔAdj-R^2)
			Developed Economies					
Australia	0.635*	0.217*	0.45	0.399*	0.122	0.657*	0.572*	0.59
	(0.000)	(0.000)	(0.36)	(0.000)	(0.592)	(0.000)	(0.000)	(0.16)
Austria	0.811*	0.186**	0.65	0.525*	0.032	0.821*	0.522*	0.72
	(0.000)	(0.010)	(0.61)	(0.000)	(0.688)	(0.000)	(0.000)	(0.14)
Netherlands	0.744*	0.050	0.53	0.573*	-0.087	0.636*	0.457*	0.59
	(0.000)	(0.412)	(0.48)	(0.000)	(0.189)	(0.000)	(0.000)	(0.16)
Singapore	0.606*	0.209*	0.44	0.454*	0.064*	0.638*	0.469*	0.55
	(0.000)	(0.000)	(0.32)	(0.000)	(0.007)	(0.000)	(0.000)	(0.16)
Sweden	0.635*	0.132*	0.46	0.438*	0.033	0.750*	0.556*	0.61
	(0.000)	(0.000)	(0.38)	(0.000)	(0.313)	(0.000)	(0.000)	(0.17)
Average increase in Adj-R^2			**0.43**					**0.16**
			Emerging Economies					
China	0.819*	0.107*	0.69	0.685*	0.008	0.430*	0.505*	0.75
	(0.000)	(0.000)	(0.60)	(0.000)	(0.417)	(0.000)	(0.000)	(0.32)
Malaysia	0.637*	0.245*	0.45	0.452*	-0.026	1.021*	0.571*	0.58
	(0.000)	(0.000)	(0.36)	(0.000)	(0.215)	(0.000)	(0.000)	(0.17)
Russia	0.663*	0.464*	0.53	0.538*	-0.046	1.031*	0.642*	0.61
	(0.000)	(0.000)	(0.42)	(0.000)	(0.308)	(0.000)	(0.000)	(0.25)
South Africa	0.700*	0.129*	0.53	0.585*	0.002	0.504*	0.333*	0.59
	(0.000)	(0.000)	(0.44)	(0.000)	(0.937)	(0.000)	(0.000)	(0.29)
Turkey	0.543*	0.231*	0.40	0.467*	0.180*	0.263**	0.346*	0.44
	(0.000)	(0.000)	(0.28)	(0.000)	(0.000)	(0.011)	(0.000)	(0.23)
Average increase in Adj-R^2			**0.42**					**0.25**
			Frontier Economies					
Argentina	0.555*	0.132***	0.30	0.514*	-0.036	0.495*	0.329*	0.38
	(0.000)	(0.053)	(0.28)	(0.000)	(0.664)	(0.000)	(0.000)	(0.22)
Nigeria	0.873*	0.290*	0.83	0.877*	-0.204	0.201***	0.148*	0.83
	(0.000)	(0.000)	(0.52)	(0.000)	(0.468)	(0.050)	(0.000)	(0.54)
Pakistan	0.821*	0.203*	0.71	0.660*	-0.034	0.813*	0.448*	0.77
	(0.000)	(0.000)	(0.59)	(0.000)	(0.421)	(0.000)	(0.000)	(0.27)
Saudi Arabia	0.777*	0.154*	0.72	0.590*	0.109*	0.362*	0.465*	0.79
	(0.000)	(0.000)	(0.57)	(0.000)	(0.000)	(0.007)	(0.000)	(0.25)
Ukraine	0.774*	0.393*	0.63	0.642*	0.036	0.667*	0.555*	0.69
	(0.000)	(0.000)	(0.51)	(0.000)	(0.638)	(0.000)	(0.000)	(0.29)
Average increase in Adj-R^2			**0.49**					**0.31**

Note: ΔAdj-R^2 is the increase in the adjusted R^2 from the static OLS to dynamic OLS model; * ** and *** indicate significance at 0.01, 0.05 and 0.10 level, respectively.

Source: Author's calculations

5.1.2.2 Wooldridge Test for Strict Exogeneity

One basic assumption of the FE estimator is that the error term is independent of all the regressors; violation of this assumption can lead to inconsistent results (Wooldridge, 2002). This phenomenon is called the problem of endogeneity that can be caused by *measurement error*, *omitted variable* (also known as un-observed heterogeneity) and *simultaneity*. Endogeneity can occur in both directions, *i.e.,* the error term is correlated with lagged values of regressor and where future values of the regressors are correlated with the current error term. The second situation resembles simultaneity. Wooldridge (2002, p 285) argues that it is easy to solve the problem of endogeneity if the error terms are correlated with lagged values of the regressors by including lags of the regressors in the model. However, the real problem is when the error terms are correlated with future values of the regressors (IC in our case). Wooldridge (2002) suggests a test that can be used to test for strict exogeneity. If $t > 2$ (which is true in this case) then the test can be written as:

$$FP_{it} = \alpha + \beta X_{it} + \gamma Z_{it+1} + \partial C_{it} + \eta_i + e_{it}, \quad t = 1,2,\ldots \quad (5.2)$$

Where Z_{it+1} are subsets of future values of IC efficiency (VAIC, HCE, SCE and CEE) and ∂ is a vector of the control variables. The null hypothesis is $\gamma = 0$, which means future IC efficiency is not correlated with current firm performance. We apply the fixed effects estimator to equation (5.2); Table 5.2 reports the results of the relationship between current firm performance and future IC efficiency, controlling for current IC efficiency and other control variables such as GDP growth and firm size. Table 5.2 shows that coefficients of future values of IC efficiency, *i.e.,* VAIC, HCE, SCE and CEE, are significantly different from zero in most markets (developed, emerging and frontier). The significance is at the 1% level in four markets, 5% in five markets and 10% in one market (see Table 5.2). The null hypothesis of the Wooldridge test for strict exogeneity can be confidently rejected. This means that future values of one or more of the regressors in our model is significantly correlated with current firm performance, which violates the assumption of strict exogeneity. This violation leads to inconsistent results in the OLS and FE estimators (Wooldridge, 2002).

5.3 Problems in the Application of Static OLS & FE to Dynamic Models

The dynamic OLS and Wooldridge Test for strict exogeneity show that the relationship between IC and firm performance is dynamic. This section discusses the types of problem that can arise if one applies static estimators such as OLS and FE to investigate the IC and firm performance relationship in the presence of endogeneity.

5.3.1 The Problem of Simultaneity

Simultaneity in equation (5.1) exists when $E(e_{it}|FP_{it}, X_{it}) \neq 0$. This implies that it is not only IC that affects firm performance but the firm's past performance also affects IC. The discussion in section (5.1) provides the theoretical and empirical evidence about how IC depends on firms' past performance (the case of simultaneity). In this case, the application of static OLS and FE will generate biased, inconsistent results (Gujarati, 2012). This problem can be solved if we measure these relationships in two separate equations where one equation measures the effect of IC on firm performance and the other equation measures the effect of firm performance on IC. This process is called simultaneous equation modelling (SEM) (Gujarati, 2012). An important assumption of SEM, however, is to have strictly exogenous instruments which is difficult to accomplish (Wintoki *et al.*, 2012).

Table 5.2 The Wooldridge Test for Strict Exogeneity with the Dependent Variable ROA

	VAIC(t)	VAIC*(t+1)*	HCE(t)	HCE*(t+1)*	SCE(t)	SCE*(t+1)*	CEE(t)	CEE*(t+1)*
Australia	0.732*	-0.100**	0.066*	-0.012	0.946*	0.040	0.678*	-0.150*
	(0.000)	(0.024)	(0.000)	(0.790)	(0.000)	(0.467)	(0.000)	(0.000)
Austria	0.169***	-0.009	-0.195**	-0.089	1.501*	0.709**	0.575*	0.291***
	(0.054)	(0.913)	(0.034)	(0.341)	(0.000)	(0.011)	(0.000)	(0.090)
Netherlands	0.003	0.037	-0.025*	-0.203**	1.198*	1.020*	0.681*	0.292**
	(0.963)	(0.681)	(0.001)	(0.035)	(0.000)	(0.000)	(0.000)	(0.011)
Singapore	0.624*	0.202*	0.038	0.041	1.152*	0.645*	0.759*	0.276*
	(0.000)	(0.000)	(0.263)	(0.337)	(0.000)	(0.000)	(0.000)	(0.000)
Sweden	0.208**	0.080	-0.113	0.056	1.420*	0.254*	0.785*	0.145**
	(0.012)	(0.328)	(0.140)	(0.534)	(0.000)	(0.001)	(0.000)	(0.031)
China	0.610*	0.339*	0.183*	0.093*	0.910*	-0.225*	0.841*	-0.068*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Malaysia	0.498*	0.257*	-0.011	0.088*	1.355*	0.448*	0.913*	0.229*
	(0.000)	(0.000)	(0.676)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Russia	1.069*	0.186**	0.056	0.029	1.515*	-0.170	0.881*	-0.042
	(0.000)	(0.014)	(0.464)	(0.722)	(0.000)	(0.102)	(0.000)	(0.569)
South Africa	0.402*	0.165*	-0.219*	-0.081	1.392*	0.743*	0.676*	0.182*
	(0.000)	(0.000)	(0.000)	(0.101)	(0.000)	(0.000)	(0.000)	(0.002)
Turkey	0.349*	0.127**	0.094	0.046	0.521*	0.152	0.405*	0.182**
	(0.000)	(0.012)	(0.246)	(0.454)	(0.007)	(0.337)	(0.000)	(0.012)
Argentina	0.274**	-0.102	-0.095	0.037	0.886*	-0.136	0.347*	-0.233**
	(0.010)	(0.281)	(0.463)	(0.755)	(0.000)	(0.561)	(0.000)	(0.031)
Nigeria	0.379*	-0.128	0.152	-0.228	0.168	-0.001	0.184*	-0.043
	(0.003)	(0.340)	(0.814)	(0.738)	(0.560)	(0.990)	(0.005)	(0.560)
Pakistan	0.630*	0.203**	0.107***	0.253*	1.122*	0.536**	1.060*	0.196**
	(0.000)	(0.011)	(0.098)	(0.009)	(0.000)	(0.020)	(0.000)	(0.021)
Saudi Arabia	0.992*	-0.029	0.163***	-0.103	1.286*	0.854*	0.997*	-0.192**
	(0.000)	(0.703)	(0.054)	(0.231)	(0.000)	(0.000)	(0.000)	(0.025)
Ukraine	0.752*	0.279**	-0.058	0.173	1.575*	0.214	0.923*	-0.330*
	(0.000)	(0.017)	(0.594)	(0.192)	(0.000)	(0.298)	(0.000)	(0.006)

Note: * ** and *** indicate significance at 0.01, 0.05 and 0.10, respectively.

Source: Author’s calculations

5.3.2 Problem of Unobserved Heterogeneity

The second source of endogeneity is unobserved heterogeneity *i.e.* there are some other firm specific factors such as image of the firm, leverage, etc. which might affect firm performance as well as IC. The fixed part of this unobserved heterogeneity can however be solved by applying FE estimator to the linear model (Wintoki *et al.*, 2012). But, as argued by Baltagi (2008) FE estimator will only produce unbiased results if the current values of independent variable (IC and its components) are independent of past values of the dependent variable (firm performance in our case). However, future IC efficiency is significantly correlated with firm past performance in our study (see section 5.1.2.2), thus the application of FE will lead to inconsistent results (Baltagi, 2008).

The previous discussion so far in sections 5.1 to 5.2 posit some important facts such as, firstly, the relationship between IC and firm performance is dynamic in nature. Secondly, lagged firm performance is also an explanatory variable in our model. Moreover, there is reverse causal relationship *i.e.* IC efficiency also gets affected by past firm performance which is the case of simultaneity. Apart from these problems, as discussed in chapter 4 there are also problems of heteroscedasticity and autocorrelation in our data. We also discussed in chapter 4 that how these problems of heteroscedasticity and autocorrelation can be resolved without applying dynamic panel data estimator. But our supposition in chapter 4 about the dynamic relationship and endogeneity is proved true in our sections 5.1 to 5.2. This means now we need to develop a model which can not only resolve the problems of heteroscedasticity and autocorrelation but also can deal with endogeneity (mainly because of simultaneity) and dynamic nature of this relationship.

In the next section we develop a dynamic panel model which addresses endogeneity (mainly because of simultaneity and unobserved heterogeneity), heteroscedasticity and autocorrelation in our data. Equation (5.1) shows the basic characteristic of the dynamic panel model with lagged values of dependent variables as regressors (Gujarati, 2012). It is therefore important, first, to check how many lags of firm performance can capture the complete effect of past performance for the completeness of the dynamic model.

5.4 How Many Lags of Firm Performance are Significant?

Any statistical model that contains lagged dependent variables as a regressors is called a dynamic model; it should be estimated with dynamic estimation techniques (Gujarati, 2012). In other words, one should take into account the effect of past values of the dependent variable (firm performance in this case). An important question here is: “How many lags of the dependent variable should be included as the regressor?” This is particularly important because if one uses too few lags then this might not capture the complete effect of past on the present (Wintoki *et al.*, 2012). This implies that equation (5.1) is still misspecified. Another reason for needing to know how many lags are significant is that these lags can be used as instruments if we use dynamic panel data estimator. Different authors have different opinions in this regard. For example, Glen *et al.* (2001) argue that generally two lags are sufficient to capture the effect of past on future in dynamic panel models. Nevertheless, to determine how many lags are significant in this current study, we regress current firm performance on past firm performance after controlling for IC, its components and control variables. We estimate the following equation:

$$FP_{it} = \alpha + \beta_1 LFP_{it-p} + \beta_2 Z_{it} + \partial X_{it} + \eta_i + \varepsilon_{it} \text{ .... (5.3)}$$

Where LFP_{it-p} is lagged firm performance (t = 2013, 2012, ….) and Zit is a vector of independent variables (VAIC, HCE, SCE and CEE) and ∂ is a vector of control variables. Following Wintoki *et al.* (2012), we apply dynamic OLS to equation (5.3). We first include two lags. Table 5.3 shows the first two lags are significant at the 1% level in almost all 15 markets (developed, emerging and frontier). We re-run equation (5.3) dropping the recent lags of firm performance (1&2) and include a third and fourth lag. The third and fourth column in Table 5.3 shows that these older lags (3^{rd} & 4^{th}) are also significant at the 1% and 5% level in most markets, which is a good sign because these deeper lags can be used to find optimal instruments. However, when we include all four lags at the same time, un-tabulated results show that the first lag is still significant (at 1%) in all markets whereas the second lag is significant (at 5%) in almost half of the markets. The adjusted R^2 is fairly high in all specifications which shows the goodness of fit in our model. Arellano and Bond (1991) argue that the use of one lag is compulsory in dynamic panel estimation but one can use more lags to identify good instruments. However, one has to be careful in using more lags, which can reduce the data set. Thus caution should be exercised. Though deeper lags contain relevant information but, following Wintoki *et al.* (2012), we assume that the information is subsumed in the most recent lags, *i.e.,* the first lag. Hence, we use the first lag as a regressor in our dynamic estimation and deeper lags, *i.e*. 2^{nd}, 3^{rd} and 4^{th}, are used for GMM and IV style instruments.

Table 5.3 Lags of Firm Performance with ROA as the Dependent Variable

	Model 1 = VAIC					Model 2 = HCE, SCE, CEE				
	t-1	*t-2*	*t-3*	*t-4*	Adj-R^2	*t-1*	*t-2*	*t-3*	*t-4*	Adj-R^2
Developed Economies										
Australia	0.424*	0.216*	0.140*	0.055	0.57	0.296*	0.139*	0.091*	0.036	0.65
	(0.000)	(0.000)	(0.000)	(0.090)		(0.000)	(0.000)	(0.004)	(0.216)	
Austria	0.598*	0.053*	0.099	0.234**	0.73	0.424*	0.005	-0.018	0.153	0.78
	(0.000)	(0.009)	(0.449)	(0.043)		(0.000)	(0.964)	(0.874)	(0.151)	
Netherlands	0.492*	0.229*	0.022	0.173**	0.54	0.417*	0.163**	0.025	0.137**	0.60
	(0.000)	(0.002)	(0.767)	(0.013)		(0.000)	(0.019)	(0.720)	(0.036)	
Singapore	0.511*	0.163*	0.076**	0.006	0.47	0.404*	0.117*	0.065**	-0.017	0.55
	(0.000)	(0.000)	(0.018)	(0.809)		(0.000)	(0.000)	(0.027)	(0.462)	
Sweden	0.599*	0.043**	0.148*	0.090**	0.67	0.468*	0.030**	0.097**	0.070**	0.73
	(0.000)	(0.030)	(0.000)	(0.020)		(0.000)	(0.023)	(0.010)	(0.044)	
Emerging Economies										
China	0.804*	0.009	0.059*	0.009	0.67	0.643*	0.012	0.066*	0.043*	0.72
	(0.000)	(0.535)	(0.000)	(0.439)		(0.000)	(0.398)	(0.000)	(0.000)	
Malaysia	0.572*	0.100*	0.131*	-0.007	0.55	0.432*	0.069*	0.116*	-0.008	0.64
	(0.000)	(0.001)	(0.000)	(0.764)		(0.000)	(0.012)	(0.000)	(0.709)	
Russia	0.548*	0.107*	0.087*	0.091*	0.65	0.449*	0.103*	0.066**	0.080*	0.71
	(0.000)	(0.000)	(0.002)	(0.000)		(0.000)	(0.000)	(0.011)	(0.001)	
South Africa	0.527*	0.143*	0.124**	0.065	0.60	0.386*	0.146**	0.123**	0.069	0.66
	(0.000)	(0.007)	(0.020)	(0.129)		(0.000)	(0.003)	(0.012)	(0.082)	
Turkey	0.476*	0.096**	-0.001	0.249*	0.61	0.428*	0.078**	-0.006	0.229*	0.63
	(0.000)	(0.031)	(0.979)	(0.000)		(0.000)	(0.037)	(0.859)	(0.000)	
Frontier Economies										
Argentina	0.628*	0.124**	0.168**	0.148*	0.55	0.525*	0.077**	0.156**	0.158*	0.65
	(0.000)	(0.039)	(0.015)	(0.005)		(0.000)	(0.003)	(0.011)	(0.001)	
Nigeria	0.882*	0.118	0.033	-0.085	0.90	0.896*	0.123	0.044	-0.081	0.89
	(0.000)	(0.414)	(0.764)	(0.440)		(0.000)	(0.408)	(0.705)	(0.485)	
Pakistan	0.573*	0.194*	0.135**	-0.045	0.79	0.448*	0.150*	0.142*	-0.059	0.84
	(0.000)	(0.001)	(0.017)	(0.297)		(0.000)	(0.003)	(0.005)	(0.129)	
Saudi Arabia	0.778*	-0.008	0.030	0.797**	0.83	0.683*	-0.006	0.006	0.083**	0.85
	(0.000)	(0.860)	(0.526)	(0.033)		(0.000)	(0.894)	(0.903)	(0.019)	
Ukraine	0.759*	0.092**	0.037	0.017	0.76	0.577*	0.081*	0.067	0.014	0.82
	(0.000)	(0.017)	(0.517)	(0.692)		(0.000)	(0.003)	(0.181)	(0.709)	

Note: * and ** represent significance at 0.01 and 0.05 level, respectively.

Source: Author's calculations

5.5 The Dynamic Panel Data Estimation: Model and Results

Endogeneity (because of simultaneity and unobserved heterogeneity) restricts the use of static OLS or FE estimator because these estimators produce biased results (Wintoki *et al.*, 2012). Therefore, we developed the dynamic panel data (DPD) estimation model that can incorporate the dynamic nature of the relationship between IC and firm performance and produce unbiased results.

A dynamic panel model including lagged firm performance can be written as:

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 VAIC_{it} + \beta_3 Control_{it} + T.\lambda + \eta_i + \varepsilon_{it} \text{ .... (5.4)}$$

Where FP is firm performance, T.λ is a vector of year dummies, η is unobserved firm specific effects and ε is error term. Equation (5.4) for individual components of VAIC can be written as:

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 HCE_{it} + \beta_3 SCE_{it} + \beta_4 CEE_{it} + \beta_5 Control_{it} + T.\lambda + \eta_i + \varepsilon_{it} \text{ ..(5.5)}$$

To estimate equations (5.4) and (5.5), we select the Arrelano-Bond generalised method of moments (GMM) as the estimation method. We select this estimation technique for several reasons discussed in the next section.

5.5.1 Justification of the Arrelano - Bond GMM Estimator

Baltagi (2008) argues that dynamic panel models have at least two unique characteristics. First, these models contain autocorrelation because of the presence of lagged dependent variables among the regressors (LFP_{it-1} in equations (5.4) and (5.5). Secondly, these models also are characterized with endogeneity (mainly because of simultaneity) problem. The first characteristic posits that if FP_{it} is a function of ε_{it} then FP_{it-1} is also function of ε_{it}, which means that FP_{it-1} (as a regressor) is correlated with the error term. In this case the application of OLS is not only biased but also inconsistent even if ε_{it} is not serially correlated. Similarly, the FE estimator can eliminate firm specific fixed effects (η_i) in our models, but FP_{it-1} will still be correlated with ε_{it}, which makes the FE estimation inappropriate in the dynamic panel models (Baltagi, 2008). More precisely, Wooldridge (2010) states that the application of FE in equations (5.4) and (5.5) could produce the following bias.

$$\frac{1}{T}\sum_{t-1}^{T} E(Z_{it}'\varepsilon_{it}) = -\frac{1}{T}\sum_{t-1}^{T} E(\overline{Z}_{it}'\varepsilon_{it}) = -E(\overline{Z}_i'\varepsilon_i) \text{ ..... (5.6)}$$

Where Z is $Z - \overline{Z}$ and *Z* is current year values of the independent variables such as VAIC, HCE, SCE and CEE. Equation (5.6) implies that if the current values of regressors are positively (negatively) correlated with past values of firm performance then the FE of current values of firm performance on current values of IC will be negatively (positively) biased.

A well-developed GMM estimator by Arellano and Bond (1991) can produce consistent results solving all the econometrics in dynamic panel models (equations 5.4 & 5.5). The following points explain how GMM can resolve the issues and why this estimator is most appropriate for this current study.

(a) GMM is an appropriate estimator when there is heteroscedasticity (individuals with varying size and different characteristics) in the data (Baltas *et al.*, 2003). This is true in this case because publicly listed firms in our data can be of varying size. In chapter 4, we applied the *Bruesch-Pagan* Test which shows that there is heteroscedasticity in the data. Therefore, GMM is an appropriate estimator because it allows the disturbance term to be non-constant (Arellano & Bond, 1991).

(b) GMM wipes out firm specific fixed effects by taking the first difference of the variables. In the first differencing, the first observation of each variable is subtracted from the second value and so on. Our dynamic models can be written in the first difference form as:

$$\Delta FP_{it} = \alpha + \Delta\beta_1 VAIC_{it} + \Delta\beta_2 \partial Control_{it} + T.\lambda + \Delta\varepsilon_{it} \text{ .... } (5.7)$$

$$\Delta FP_{it} = \alpha + \Delta\beta_1 HCE_{it} + \Delta\beta_2 SCE_{it} + \Delta\beta_3 CEE_{it} + \Delta\beta_4 \partial Control_{it} + T.\lambda + \Delta\varepsilon_{it} \text{ .. } (5.8)$$

Where $\Delta FP_t = (FP_t - FP_{t-1})$ and $\Delta\varepsilon_t = (\varepsilon_t - \varepsilon_{t-1})$ for firm *i*.

(c) In the GMM instrument, the lagged values of the dependent variables (first-differenced) with its past levels which solve the problem of autocorrelation. Since we have tested for the presence of autocorrelation in chapter 4, GMM is an appropriate estimator in this current study (Baltagi, 2008).

(d) GMM exploits the dynamic nature of the relationship by using instruments to produce consistent, unbiased results (Wintoki *et al.*, 2012) which again make it an appropriate estimator for our study.

(e) Based on Arrelano and Bond's (1991) work, Blundell and Bond (1998) proposed a system of GMM (SGMM) that can use a level equation in addition to a differenced equation to increase the efficiency of the results, especially in data with a smaller time dimension. SGMM is also an efficient estimator when the variables in levels are weak instruments for the first-difference equation. The use of the level equation also increases one other assumption of SGMM about the exogeneity of the instruments.

(f) Another important aspect of GMM or SGMM is that these estimators use lagged values of dependent or independent variables as instruments. This means that all necessary information (to be used as instruments) comes from the firms' history (Arellano & Bond, 1991; Blundell & Bond, 1998). This characteristic is particularly important when one cannot find strictly exogenous instruments from outside the dataset. In other words, SGMM allows us to use instruments from within the existing dataset.

5.5.2 Dynamic Panel Data Estimation: System GMM Results

This section reports the results of the two step robust system GMM estimates of the relationship between IC and firm performance. We apply the two step SGMM instead of one step because Roodman (2006) argues that two step yields a robust covariance matrix with respect to autocorrelation and heteroscedasticity. Another reason is that the two step method produces the *Sargan Test* (robust *Hensen J-Test*), which is not available in the one step SGMM estimation. Tables 5.4 and 5.5 and Appendix Tables E1 and E2 present SGMM results for all 15 markets (developed, emerging and frontier), with ROA, ROE, ATO and P/B as independent variables, respectively. Table 5.4 shows IC efficiency in terms of VAIC is positive and significant at the 1% level in 11 markets and at 5% level in two markets. These findings support our basic argument that IC contributes significantly towards the firm performance in developed and emerging markets with the exception of the Netherlands. The significant relationship between IC and firm performance in the Netherland in the OLS estimation could be the result of spurious regression. The findings from the SGMM estimation are consistent with previous VAIC studies, Clarke *et al.* (2011) for Australia, Vishnu and Kumar Gupta (2014) for India, Chen *et al.* (2005) for Taiwan, and Ting and Lean (2009) for Malaysia.

Table 5.4 The Dynamic Panel-Data Estimation: the Two Step Robust System GMM Results with ROA as the Dependent Variable

	Model 1		Model 2			
	L.ROA	VAIC	L.ROA	HCE	SCE	CEE
			Developed Economies			
Australia	0.324*	0.370*	0.257*	0.025	0.825*	0.708*
	(0.000)	(0.005)	(0.000)	(0.761)	(0.000)	(0.000)
Austria	0.509*	0.290**	0.325*	-0.011	1.154*	0.710*
	(0.000)	(0.029)	(0.000)	(0.893)	(0.000)	(0.000)
Netherlands	0.291**	0.565	0.344*	-0.192	0.918*	0.586*
	(0.027)	(0.138)	(0.000)	(0.203)	(0.000)	(0.000)
Singapore	0.046	0.297*	0.224*	0.029	0.886*	0.589*
	(0.764)	(0.000)	(0.003)	(0.493)	(0.000)	(0.000)
Sweden	0.247**	0.303*	0.177**	0.199**	0.846*	0.781*
	(0.022)	(0.000)	(0.043)	(0.016)	(0.000)	(0.000)
			Emerging Economies			
China	0.564*	0.478*	0.653*	-0.346**	1.225*	0.561*
	(0.000)	(0.005)	(0.000)	(0.038)	(0.001)	(0.000)
Malaysia	0.442*	0.326*	0.227*	-0.173	1.520*	0.755*
	(0.000)	(0.005)	(0.000)	(0.149)	(0.000)	(0.000)
Russia	0.646*	0.544*	0.507*	-0.148	0.855**	0.423**
	(0.000)	(0.004)	(0.001)	(0.715)	(0.020)	(0.041)
South Africa	0.397*	0.219**	0.231*	-0.010	0.889*	0.522*
	(0.000)	(0.012)	(0.001)	(0.901)	(0.000)	(0.000)
Turkey	0.225**	0.305*	0.099	0.233*	0.428*	0.533*
	(0.022)	(0.000)	(0.216)	(0.000)	(0.004)	(0.000)
			Frontier Economies			
Argentina	0.411*	0.200	0.467*	-0.360	0.866*	0.361*
	(0.000)	(0.234)	(0.000)	(0.120)	(0.003)	(0.000)
Nigeria	0.778*	0.333*	0.760*	-0.297	0.223	0.193*
	(0.000)	(0.000)	(0.000)	(0.518)	(0.154)	(0.001)
Pakistan	0.531*	0.538*	0.463*	-0.054	1.035*	0.642*
	(0.000)	(0.001)	(0.000)	(0.282)	(0.000)	(0.000)
Saudi Arabia	0.407*	0.334*	0.391*	0.145*	0.459**	0.651*
	(0.001)	(0.000)	(0.000)	(0.007)	(0.037)	(0.000)
Ukraine	0.613*	0.801*	0.489*	0.193	0.763*	0.706*
	(0.000)	(0.001)	(0.000)	(0.240)	(0.001)	(0.000)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10, respectively. Control variables and time dummies are included in all specifications.

Source: Author's calculations

Table 5.5 The Dynamic Panel-Data Estimation: the Two Step Robust System GMM Results with ROE as the Dependent Variable

	Model 1		Model 2			
	L.ROE	VAIC	L.ROE	HCE	SCE	CEE
			Developed Economies			
Australia	0.277*	0.455*	0.225*	0.089	0.693*	0.588*
	(0.000)	(0.004)	(0.000)	(0.391)	(0.000)	(0.000)
Austria	0.281**	0.233***	0.193**	-0.164**	0.853*	0.407*
	(0.032)	(0.092)	(0.042)	(0.023)	(0.000)	(0.000)
Netherlands	0.300*	0.105	0.240**	-0.202	0.801*	0.384*
	(0.004)	(0.441)	(0.015)	(0.174)	(0.000)	(0.000)
Singapore	0.052	0.347*	0.207*	-0.018	1.029*	0.609*
	(0.701)	(0.000)	(0.000)	(0.692)	(0.000)	(0.000)
Sweden	0.198***	0.246**	0.157**	0.011	0.908*	0.591*
	(0.071)	(0.011)	(0.017)	(0.907)	(0.000)	(0.000)
			Emerging Economies			
China	0.396*	0.707*	0.287*	-0.175**	1.065*	0.724*
	(0.000)	(0.002)	(0.000)	(0.033)	(0.000)	(0.000)
Malaysia	0.407*	0.458*	0.206*	-0.015	1.290*	0.716*
	(0.000)	(0.000)	(0.000)	(0.910)	(0.000)	(0.000)
Russia	0.346*	0.699**	0.448*	-0.180	1.302*	0.703*
	(0.000)	(0.020)	(0.000)	(0.380)	(0.000)	(0.000)
South Africa	0.394*	0.209**	0.151**	-0.011	0.980*	0.549*
	(0.000)	(0.024)	(0.049)	(0.878)	(0.000)	(0.000)
Turkey	0.207***	0.204*	0.042	0.045	0.626*	0.485*
	(0.052)	(0.000)	(0.524)	(0.445)	(0.000)	(0.000)
			Frontier Economies			
Argentina	0.505*	0.245***	0.419*	-0.220	0.719*	0.483*
	(0.000)	(0.093)	(0.000)	(0.247)	(0.003)	(0.000)
Nigeria	0.709*	-0.167**	0.552*	-0.660***	0.296*	-0.208**
	(0.000)	(0.026)	(0.000)	(0.076)	(0.006)	(0.037)
Pakistan	0.512*	0.321*	0.398*	-0.123**	1.236*	0.526*
	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)
Saudi Arabia	0.447*	0.175*	0.302*	-0.008	0.853*	0.716*
	(0.000)	(0.000)	(0.000)	(0.806)	(0.000)	(0.000)
Ukraine	0.540*	0.703*	0.379*	0.109	0.827*	0.763*
	(0.007)	(0.006)	(0.000)	(0.455)	(0.001)	(0.000)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10, respectively. Control variables and time dummies are included in all specifications.

Source: Author's calculations

With the exception of Argentina, Table 5.4 shows VAIC is significant and positively related to ROA in frontier markets at the 5% level. The relationship for Argentina is significant in the static models (OLS & FE) but insignificant in SGMM. Considering VAIC is an accurate measure of IC efficiency (further discussed in the next chapter) these findings are in line with the RB theory. The RB theory argues that IC forms a sustainable competitive advantage for the firm. Our findings endorse this theory that IC significantly contributes towards the financial performance of a firm, which can help the firm to yield above average returns. This also confirms the argument of Kolachi and Shah (2013) that IC is important for all types of firm (big or small) in all types of market (developed or underdeveloped). Zéghal and Maaloul (2010) state that firms can yield extra returns and build a competitive advantage from the effective use of their strategic resources such as IC assets. Our findings are consistent with Zéghal and Maaloul (2010)'s argument, which means when IC efficiency increases, a firm's performance (ROA) also increases.

The individual component (HCE, SCE and CEE) analysis shows that HCE is insignificant in almost all markets (developed, emerging and frontier); the exceptions are one developed (Sweden), two emerging (China and Turkey) and one frontier (Saudi Arabia) market, which show a weak or negative significant relationship with ROA. This relationship between HCE and ROA was positive and significant in previous studies (Young *et al.*, 2009; Clarke *et al.*, 2011; Vishnu & Kumar Gupta, 2014) which are based on static (OLS and FE) estimators. Our results are consistent with previous studies (Rehman *et al.*, 2011; Alipour, 2012; Mehralian *et al.*, 2012) which show a negative or no significant relationship between HCE and ROA. These findings suggest that firms in most markets, regardless of the economic development stage, treat investment in human capital as expenditure. Our findings cannot endorse the *Resource Dependency (RD)* theory which argues that firms should utilize their available human resources to increase the value creation of the firm.

The basic argument by Pulic (2004), while developing the VAIC model, was that money spent on humans within the firm should be treated as investment instead of expense. He argues that human resources create value for the firm just like other assets such as land and buildings. Therefore, if spending on those tangible assets are investments then spending on human resources should also be treated as long term investments. This is why Pulic (2004) does not include salaries and wages as expenses in calculating value added (VA). This contradictory result (where our findings are differ from theory) gives rise to two possible scenarios. First, it raises doubts on the reliability of the VAIC model to measure the efficiency of individual components (HCE, SCE and CEE) accurately. It is noteworthy that the measurement of the VAIC model in general and its two components, *i.e.*, HCE and SCE, in particular, have been criticised by Ståhle *et al.* (2011). In the next chapter, we further discuss criticisms of the VAIC model and modify the original VAIC model. Secondly, since the firm's owners (shareholders) hire and pay employees to act on their behalf, that spending is treated as expenditure. That is why these investments are recorded on the expense side of conventional accounting statements (income statement). Some pioneers in the IC field such as Edvinsson and Malone (1997), suggest firms produce separate statements for IC assets. We discuss and test the reliability of the VAIC model in next chapter.

Table 5.4 shows SCE and CEE are positive and significantly related to ROA at the 1% and 5% level in 14 markets; the exception is Nigeria for which no significant relationship was found between SCE and ROA. These findings suggest that firms in all types of market accumulate and utilize SC and CE quite efficiently for the value creation. Our findings, in terms of SCE, agree with the OL theory. Njuguna (2009) states that organizational learning is a process whereby a firm can acquire a new wealth of knowledge that can be translated into innovation and protected in the form of unique processes, models and copyrights. Our findings suggest that firms can transform their structural capital resources into innovation that, in turn, increases the firm's profitability. Our findings in terms of physical capital (CEE) support the general argument that physical assets are vital resources for the firm to create value (Firer & Williams, 2003; Chan, 2009b; Ting & Lean, 2009; Young *et al.*, 2009; Vishnu & Kumar Gupta, 2014).

The analysis extends to another performance measure, *i.e.,* ROE for a robustness check. Table 5.5 shows ROE, used as a performance measure, produces quite similar results to ROA. The relationship between VAIC and ROE is positive and statistically significant at the 1% level in eight markets, 5% level in four markets and 10% level in two markets (Table 5.5), which means IC increases firm profitability (measured in terms of ROE). The individual components of VAIC analysis produces similar results where HCE is insignificant with ROE in 11 markets. SCE and CEE are positive and significantly related to ROE in all 15 markets at the 5% level. Our findings of SGMM estimation are consistent with some studies (Clarke *et al.*, 2011; Kai *et al.*, 2011; Vishnu & Kumar Gupta, 2014) with only VAIC and CEE are positive and significantly related to firm performance in terms of ROE. These studies used static measures (OLS & FE). The findings again endorse RD theory that IC resources contribute significantly toward firm performance in terms of ROE and ROA.

We also extend our analysis to other dimensions of firm performance, *i.e.,* productivity and market measure (ATO & P/B) to test whether there are any differences in the results when performance is measured in terms of productivity or asset utilization (ATO) and market valuation (P/B). Appendix Tables E1 and E2 show the relationships between IC and ATO and P/B, respectively. These results are quite different from ROA and ROE. The results show IC efficiency is neither significantly related to ATO nor to P/B. However, CEE of the individual components is statistically significant (at 10% or less) with ATO and P/B. These results are consistent with previous studies (Firer & Williams, 2003; Kai *et* *al.*, 2011; Mehralian *et al.*, 2012; Gigante, 2013) that report that IC is significantly related to ROA and ROE but weakly or not related to either ATO or P/B.

P/B exhibits two unique characteristics. First, the measure is mostly favoured by investors when making investment decisions. Investors are mostly concerned with the physical resources a firm holds; IC resources are least important to them (Firer & Williams, 2003). Another possible explanation could be that since P/B is based on the closing price on the stock exchange, it might not depict the true situation of the market.

The results from SGMM estimation are mostly consistent to those of the static estimators (OLS and FE) with the exception of HCE, which is significantly related to performance measure but insignificant in this study. Before we generalize these results, it is pertinent to mention that like OLS and FE, SGMM estimations are subject to various diagnostic tests. As argued by Baltagi (2008) and Roodman (2006), one should test the reliability of SGMM results through various tests such as autocorrelation, and validity of instruments. The next section reports and discusses diagnostic tests of SGMM estimators.

5.6 Dynamic Panel Data Estimation: Tests of the Specifications

As discussed in section 5.4.1, SGMM is the most appropriate estimator for this current study. It is also discussed there how this estimator can solve most econometric problems embedded in our data set. These problems range from heteroscedasticity to endogeneity, which can be resolved through the application of SGMM. How reliable are the SGMM estimations? Roodman (2006) and Baum (2006) argue that one should perform diagnostic tests of SGMM to check the reliability of the estimator. In this section, we perform some validity tests of SGMM estimations based on the literature.

5.6.1 First-Order (AR1) and Second-Order (AR2) Autocorrelation Tests

Arellano and Bond (1991) argue that the SGMM estimator requires first-order autocorrelation but not second-order autocorrelation in the error term. They recommend checking the AR (1) and AR (2) diagnostic tests. The null hypothesis under both tests is that there is no autocorrelation in first and second-order for AR (1) and AR (2), respectively, therefore one should strictly not reject the null hypothesis in AR (2). The p-values for the AR (2) test are well above any conventional significance level (see Tables 5.6 and 5.7 and Appendix Tables F1and F2). We cannot reject the null hypothesis which means that there is no second-order serial correlation. The p-values of AR (1) are significant at the 5% level which means that there is first-order autocorrelation – which is required in the SGMM estimator.

5.6.2 The Hansen J. Test for Over-Identification of Instruments

The validity of the instruments used in SGMM is very important since SGMM can easily over-identify instruments that violate the assumptions of SGMM. Baum (2006) argues that the Hansen J. Test is robust in the case of SGMM to test the over-identification restrictions. The null hypothesis under this test is that over identifying restrictions are true and instruments are exogenous. Column three in Tables 5.6 and 5.7 and Appendix Tables F1 and F2 show that the *p-values* of the Hansen J. Test are well above any conventional significance level so we cannot reject the null hypothesis. This implies that the instruments used in our SGMM estimation are valid and/or correctly identified (Roodman, 2006).

5.6.3 The Difference-in-Hansen Test of Exogeneity

As discussed in section 5.1.1, SGMM bears an additional assumption of exogeneity of lagged differences as instruments, hence it is important to test this assumption. Baum (2006) and Roodman (2006) suggest that this assumption can be tested with the Difference-in-Hansen Test. The null hypothesis of this test is that the subset of instruments (lagged differences) are exogenous. The fourth column in Tables 5.6 and 5.7 and Appendix Tables F1 and F2 report the p-values of the Difference-in-Hansen Test. The results show no evidence to reject the null hypothesis which implies that all subsets of the instruments used in SGMM are strictly exogenous.

5.6.4 The Assumption of Steady State

One can also check for the validity of the instruments in SGMM through the "steady state" assumption (Roodman, 2006). Under this assumption one should test the systematic relationship between deviation from long-term values and fixed effects. This means that the coefficients of the lagged dependent variables should be less than absolute value of one. The results in Tables 5.4 and 5.5 and Appendix Tables E1 and E2 show the coefficients of all lagged dependent variables (ROA, ROE, ATO and P/B) are less than one (unity), which means the steady-state assumption holds (Roodman, 2006).

5.6.5 Instruments Count Method

Roodman (2006) suggests that one should always report the number of instruments included in the SGMM estimation. The number of instruments, according to Roodman (2006), is another way to check the validity of the results of SGMM. The rule of thumb is that the number of instruments should always be less than the number of observations. The results in Table 5.6 and 5.7 and Appendix Tables F1 and F2 show the number of instruments are less than the number of observations in all cases which fulfils one of the assumptions of SGMM.

Thus the diagnostic tests verify the validity of SGMM estimation and hence provide sufficient evidence that our results from SGMM estimation are efficient, consistent and unbiased.

Table 5.6 The Dynamic Panel-Data Estimation: Diagnostic Tests with the Dependent Variable ROA

	Model 1 (VAIC)						Model 2 (HCE,SCE,CEE)					
	AR1	AR2	Han.J. O.Id.	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id.	Han.J. Diff	No. INS	Obs.
Developed Economies												
Australia	0.000	0.231	0.522	0.520	34	2563	0.000	0.321	0.118	0.563	68	2563
Austria	0.024	0.883	0.531	0.597	60	378	0.023	0.650	0.681	0.762	68	378
Netherlands	0.009	0.320	0.134	0.182	41	468	0.002	0.062	0.300	0.223	68	468
Singapore	0.028	0.759	0.415	0.769	30	3058	0.000	0.190	0.140	0.506	84	3058
Sweden	0.021	0.709	0.157	0.760	48	1232	0.000	0.398	0.138	0.638	68	1232
Emerging Economies												
China	0.000	0.313	0.315	0.401	42	9599	0.000	0.979	0.100	0.235	60	9599
Malaysia	0.000	0.981	0.145	0.070	60	4012	0.000	0.657	0.451	0.153	68	4012
Russia	0.000	0.052	0.064	0.994	42	2724	0.100	0.314	0.424	0.107	52	2724
South Africa	0.000	0.449	0.167	0.384	34	1166	0.000	0.221	0.228	0.812	68	1166
Turkey	0.000	0.141	0.269	0.541	34	1014	0.000	0.204	0.390	0.278	68	1014
Frontier Economies												
Argentina	0.064	0.223	0.254	0.516	60	348	0.026	0.255	0.286	0.383	68	348
Nigeria	0.000	0.381	0.342	0.895	34	304	0.001	0.996	0.567	0.303	68	304
Pakistan	0.000	0.556	0.491	0.970	34	921	0.000	0.570	0.522	0.235	68	921
Saudi Arabia	0.045	0.373	0.360	0.654	48	636	0.022	0.256	0.254	0.062	68	636
Ukraine	0.000	0.224	0.120	0.772	60	920	0.000	0.354	0.095	0.086	96	920

Note: AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively. Han.J,O.Id is the Hansen J. Test for over identification of instruments. Han.J.Diff is the Difference-in-Hansen test for exogeneity of instruments; No. INS is the number of instruments used in each specification and Obs is the number of observations.

Source: Author's calculations

Table 5.7 The Dynamic Panel-Data Estimation: Diagnostic Tests with the Dependent Variable ROE

	Model 1 (VAIC)						Model 2 (HCE,SCE,CEE)					
	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.
					Developed Economies							
Australia	0.000	0.268	0.439	0.467	34	2541	0.000	0.350	0.255	0.904	68	2541
Austria	0.057	0.638	0.229	0.696	34	374	0.043	0.729	0.612	0.963	68	374
Netherlands	0.006	0.261	0.320	0.442	48	464	0.005	0.104	0.364	0.243	68	464
Singapore	0.019	0.686	0.473	0.231	42	3040	0.000	0.229	0.065	0.267	68	3040
Sweden	0.009	0.961	0.311	0.959	34	1219	0.000	0.781	0.655	0.582	68	1219
					Emerging Economies							
China	0.000	0.220	0.996	0.100	42	9559	0.000	0.850	0.850	0.448	84	9559
Malaysia	0.000	0.955	0.076	0.307	60	3996	0.000	0.810	0.791	0.739	68	3996
Russia	0.000	0.086	0.026	0.594	60	2672	0.000	0.340	0.150	0.953	84	2672
South Africa	0.000	0.515	0.104	0.216	34	1161	0.000	0.710	0.087	0.192	96	1161
Turkey	0.000	0.102	0.539	0.263	34	1010	0.000	0.228	0.430	0.481	68	1010
					Frontier Economies							
Argentina	0.031	0.377	0.630	0.661	34	345	0.018	0.324	0.319	0.437	68	345
Nigeria	0.049	0.051	0.709	0.204	34	325	0.049	0.086	0.489	0.382	68	325
Pakistan	0.000	0.349	0.199	0.217	34	916	0.001	0.523	0.593	0.206	68	916
Saudi Arabia	0.029	0.348	0.547	0.571	34	636	0.017	0.335	0.479	0.129	68	636
Ukraine	0.000	0.160	0.057	0.695	60	893	0.001	0.263	0.114	0.673	120	893

Note: AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively; Han.J,O.Id is the Hansen J. Test for over identification of instruments; Han.J.Diff is the Difference-in-Hansen test for exogeneity of instruments; No. INS is the number of instruments used in each specification and Obs is the number of observations.

Source: Author’s calculations

5.7 IC and Firm Performance during 2008 Global Financial Crisis

The 2008 global financial crisis was one of the worst financial turmoil in history and led many firms to rethink their strategic investments (Lin *et al.*, 2012). Globalization and turbulent effects plus a complex business environment have forced many firms to look for new ways to use available resources at maximum possible efficiency. Sumedrea (2013) argues that the 2008 global financial crisis and its after effects have forced firms' management, practitioners and scholars to analyse the relationship between a firm's financial performance and available resources. As a result, the importance of IC became more critical in the event of financial turbulence when the firms look for new skills and solutions to recover from financial crises. Sumedrea (2013) concludes that during financial crises the survival of firms can be linked to IC in terms of company development. More specifically, the intellectual resources can be used efficiently to create value during financial turmoil when firms cannot afford major investments in other physical resources.

In our understanding, published studies exploring the role of IC during financial crises are minimal (see Sumedrea (2013) & Lin *et al.* (2012)). The results of these studies are difficult to generalize since the former study covers only the Romanian economy whereas the latter study focuses on national IC in a few Asian economies. Young *et al.* (2009)'s study analyses the role of IC during the 1997 Asian financial crisis through the interaction terms of financial crisis and human and physical capital in selected Asian markets. In order to further explore the role IC during financial turmoil and to expand its scope to economically different markets (developed, emerging and frontier), we explore the role of IC during the 2008 global financial crisis. Following Young *et al.* (2009), we introduce the interaction terms of the 2008 global financial crisis with VAIC, HCE, SCE and CEE. We estimate the following regression models.

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 VAIC_{it} + \beta_3 C*VAIC_{it} + \beta_4 Control + \eta_t + \varepsilon_{it} \text{ ....(5.9)}$$

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 HCE_{it} + \beta_3 SCE_{it} + \beta_4 CEE_{it} + \beta_5 C*HCE_{it} + \beta_6 C*SCE_{it} + \beta_7 C*CEE_{it} + \beta_8 Control + \eta_t + \varepsilon_{it} \text{ ....(5.10)}$$

Where C*VAIC, C*HCE, C*SCE and C*CEE are the interaction terms between the 2008 global financial crisis (a dummy variable that has a value of 1 in 2008 and 0 otherwise) and VAIC, human capital, structural capital and physical capital. Table 5.8 reports the SGMM estimations of equation (5.9) and (5.10). The interaction terms of IC efficiency, *i.e.,* VAIC as well as its individual components (HCE, SCE and CEE) are insignificant in almost all markets (developed, emerging and frontier), which means IC efficiency was unaffected during the 2008 global financial crisis. Our results are contrary to those reported by Sumedrea (2013) and Young *et al.* (2009) where a positive, significant relationship is recorded between IC and financial crisis. For robustness purposes, we then include a dummy of 2008 (which has a value of 1 in 2008 and 0 otherwise); un-tabulated results are similar to those in Table 5.8.

Table 5.8 IC and Firm Performance During the 2008 Financial Crisis; Two Step Robust System GMM Results

Dependent Variable ROA	C*VAIC	C*HCE	C*SCE	C*CEE
	Developed Economies			
Australia	0.001	0.001	-0.351	-0.106
	(0.737)	(0.515)	(0.167)	(0.300)
Austria	0.083	0.080	-0.427	-0.134
	(0.458)	(0.518)	(0.697)	(0.656)
Netherlands	-0.017	-0.525	1.746	0.326
	(0.955)	(0.545)	(0.618)	(0.275)
Singapore	0.001	0.000	-0.260	0.453
	(0.505)	(0.967)	(0.593)	(0.243)
Sweden	-0.006	0.007	-0.317	-0.052***
	(0.814)	(0.879)	(0.559)	(0.092)
	Emerging Economies			
China	-0.002	0.001	0.962	1.829
	(0.298)	(0.407)	(0.460)	(0.445)
Malaysia	0.000	0.001	-0.304	0.199
	(0.995)	(0.312)	(0.351)	(0.433)
Russia	0.002	-0.014	2.381	1.343
	(0.715)	(0.523)	(0.169)	(0.272)
South Africa	0.002	0.000	0.401	0.296
	(0.859)	(0.982)	(0.348)	(0.110)
Turkey	0.075	0.017	-0.257	-0.249
	(0.148)	(0.487)	(0.869)	(0.636)
	Frontier Economies			
Argentina	-0.011	0.065	-1.120	0.617
	(0.696)	(0.133)	(0.401)	(0.309)
Nigeria	0.025	-12.385	24.606	-0.047**
	(0.564)	(0.428)	(0.402)	(0.021)
Pakistan	-0.120	0.014	-0.170	1.545*
	(0.182)	(0.456)	(0.895)	(0.004)
Saudi Arabia	0.001	0.002	-0.190	-0.260
	(0.415)	(0.581)	(0.740)	(0.829)
Ukraine	-0.077	-0.148	2.797	0.428
	(0.495)	(0.257)	(0.135)	(0.101)

Note: * ** and *** indicate significance at 0.01, 0.05 and 0.10 levels, respectively.

Source: Author's calculations

5.8 Chapter Summary

The theoretical and empirical evidence in this current study reveals that the relationship between IC and firm performance is dynamic. The dynamic OLS results show that there is a significant increase in adjusted R^2 from static to dynamic OLS, which reflects the dynamic nature of the relationship. The coefficients on lagged dependent variables are statistically significant at the 5% level in all markets, which provides further evidence that lagged firm performance acts as a regressor. Following Wintoki *et al.* (2012), we applied the Wooldridge Test to test for strict exogeneity in order to determine if the regressors are strictly exogenous. We include future values of VAIC and its components (HCE, SCE and CEE) to investigate the impact of current firm performance on future IC efficiency. The results of the Wooldridge Test show that current firm performance is significantly related at the 10% level to future IC efficiency in almost all 15 markets. These results provide sufficient evidence that an IC and firm performance relationship exhibit the endogeneity problem and this relationship should be estimated using dynamic models (Baltagi, 2008). Our analysis shows that IC efficiency is related to past firm performance up to 4 years but the first lag is significant in all specifications hence we use first lag of firm performance as a regressor in dynamic estimations and deeper lags as instruments.

We apply the two step SGMM estimator to estimate the dynamic relationship between IC and firm performance. The results show that VAIC is positive and significantly related to firm performance (ROA) at the 5% level in all developed and emerging markets. VAIC is also significant and positively correlated at the 5% level with ROA in four frontier markets; the exception is Argentina. The relationship in Argentina was significant in static models (OLS & FE) but insignificant in SGMM. Nevertheless, these findings endorse the RB theory that firms can use their physical as well as intangible assets efficiently for value creation. Among the individual components of VAIC, HCE is insignificant in almost all markets (developed, emerging and frontier); the exceptions are one developed (Sweden), two emerging (China and Turkey) and one frontier (Saudi Arabia) market, which show mixed results, *i.e*., an insignificant (positive) and significant (negative) relationship with ROA. The relationship between HCE and ROA is positive and significant in most previous studies (Young *et al.*, 2009; Clarke *et al.*, 2011; Vishnu & Kumar Gupta, 2014) based on static (OLS and FE) estimators.

The SCE and CEE coefficients are positive and significantly related at the 5% level to ROA in 14 markets; the exception is Nigeria. These findings suggest that firms in all types of market accumulate and utilize SCE and CEE quite efficiently for value creation. The relationship between VAIC and ROE is positive and statistically significant at the 10% level in almost all markets (developed, emerging and frontier markets), which means IC increases firm profitability when measured in terms of ROE. Individual component analysis shows similar results to ROA, *i.e.*, SCE and CEE are positive and significant (at the 5% level) whereas an insignificant relationship was found between HCE and ROE in most markets in the study. We further extended analysis to two additional performance measures. ATO and P/B, for robustness purposes. The results show that IC efficiency is neither significantly related to ATO nor to P/B. Only CEE of the individual component analysis is statistically significant with ATO and P/B. This suggests that ROA and ROE are favourable performance measures to study IC efficiency.

Diagnostic tests of SGMM, such as AR1 and AR2 for first and second order autocorrelation, the Hansen J. Test for over-identification of instruments, the difference in Hansen J. Test for exogeneity and instrument count method provide sufficient evidence that SGMM is an appropriate estimator for this study. We also analysed the relationship between IC and firm performance during the 2008 global financial crisis. The interaction terms of IC efficiency, *i.e*., VAIC and as its individual components (HCE, SCE and CEE) are statistically insignificant in almost all markets (developed, emerging and frontier). This implies that IC efficiency was unaffected during the 2008 global financial crisis. These findings were consistent when we test the robustness through a dummy variable (2008 global financial crisis), which takes a value of 1 during 2008 and 0 otherwise. This chapter shows that the IC-firm performance relationship is dynamic and measures this relationship through a dynamic estimator, *i.e*., SGMM to produce unbiased, consistent results. The next chapter discusses some potential problems of the VAIC model, criticisms of it in the literature and provides some possible adjustments to increase the accuracy of measurements of IC efficiency.

Chapter 6

Adjustments in the VAIC Model

6.1 Introduction

As discussed in chapter 3, because of some unique characteristics, the VAIC model has been extensively used to measure IC efficiency. The VAIC model, however, has also been criticised in the literature, especially for its structural capital measure. This chapter explores and examines the capabilities of the VAIC model to measure IC efficiency. The chapter also discusses some of the criticisms of the VAIC model and how this criticism can be overcome. This study makes some adjustments to the VAIC model and introduces an Adjusted-VAIC model.

The chapter is organised as follows: Section 6.1 discusses the original VAIC model and the potential estimation problems of the model. Section 6.2 explains changes made in the VAIC model by several researchers to overcome criticisms of the model. Section 6.3 presents our adjusted-VAIC (A-VAIC) model. Empirical application of an A-VAIC model and its results are discussed in section 6.4; section 6.5 presents a critical discussion of the A-VAIC model. Section 6.6 summarizes the chapter.

6.2 Understanding the VAIC Model and its Problems

The shift from physical resource-based to knowledge-based economies and the increasing gap between firms' M/B value has caused researchers to look for different models to measure the value of intangibles (Ståhle *et al.*, 2011). The quest to develop a new model has been motivated by not only the need to measure IC resources but also to manage these resources efficiently to increase value added for firms. This quest for better management of IC resources has led to several IC measurement models such as Skandia Navigator (Edvinsson & Malone, 1997) and the VAIC model by Pulic (1998). As discussed in Chapter 3, the major benefit of using monetary based models to measure IC efficiency is that these models provide numerical results that are easy to understand and compare within departments and across industries.

Among the monetary based measures, the VAIC model has been extensively used not only by researchers but also at a corporate level, to measure the efficiency of IC in the first stage[27] (Ho & Williams, 2003). In the second stage, researchers attempted to link VAIC with overall financial performance of firms. VAIC is based on the value added concept which takes into account the total value added by an entity during any given time period. Pulic (2004) argues that firms' total value

[27] VAIC model was initially used to measure only IC efficiency and later on this efficiency was linked with financial performance of the firms

added depends upon two types of capital, physical capital and IC. This is why the VAIC model is a composite measure of both physical and IC efficiencies. The calculations of the VAIC model along with its individual components, human, structural and physical capital, have been discussed in great detail in Chapter 3. The next section discusses the problem areas in the calculations of the VAIC model.

6.2.1 General Criticisms of the VAIC Model

Despite its popularity, the VAIC model has been criticised for its construction and ability to capture the full information of IC resources. The VAIC model is based on the VA concept and VA is calculated as the sum of a firm's operating profit (OP), its personnel costs (LC) and depreciation and amortization (D&A) expenses. The basic argument of Pulic (1998) is that since money spent on human resources creates value for the firm these expenses should be treated as investments – this is consistent with (Frederickson *et al.*, 2010). Ståhle *et al.* (2011) argue that OP and D&A expenses are generally affected by the decisions of firms such as OP is the outcome of current investment whereas D&A are the outcomes of previous investment. Furthermore, structural capital (SC) is calculated by subtracting personnel costs from value added (SC = VA – LC); in other words SC = OP + D&A. Ståhle *et al.* (2011) therefore state that OP + D&A is comparable to the operating margin of the firm thus there is no reason to call structural capital. Matching the concept of the VAIC model with different definitions of IC in the literature, Ståhle *et al.* (2011) argue that VAIC does not meet the full criteria for being representative of IC. However, the VAIC model has been used extensively in spite of major criticisms. Vishnu and Kumar Gupta (2014) believe that the VAIC model fairly represents important components of IC. However, there is one serious problem in the VAIC model, *i.e.,* the SCE measure of the VAIC model is not justifiable (Ståhle *et al.*, 2011; Vishnu & Kumar Gupta, 2014; Nimtrakoon & Chase, 2015). The next section discusses this problem in detail.

6.2.2 Problems in Structural Capital Efficiency Measurement

In addition to structural capital measure, the VAIC model exhibits another serious problem as far structural capital efficiency (SCE) is concerned. SEC is measured by dividing structural capital by value added (SCE = SC/VA). There are two basic problems in this calculation. First, since SC is the difference between VA and LC or human capital, thus there is perfect dependency upon each other. This means that the value of SC depends on the value of HC as shown in the equation below.

$$SC = VA - HC \text{......}(6.1)$$

Moreover:

$$HCE = VA / HC \text{......}(6.2)$$

$$SCE = SC / VA\ldots\ldots(6.3)$$

Hence SCE can also be written as:

$$SCE = 1 - 1 / HCE\ldots\ldots(6.4)$$ [28]

Similarly, HCE can also be written as:

$$HCE = 1 / (1 - SCE)\ldots\ldots(6.5)$$

This scenario leads to two problematic situations. First, because of the perfect dependency between HCE and SCE, which stems from equation (6.1), one can say that an increase in human capital will lead to a decrease in structural capital, VA being constant. Second, based on equation (6.3), one can interpret that an increase in VA will lead to a decrease in structural capital efficiency, which is against the basic principles of finance[29]. Because of the severity of the problems with SCE in the VAIC model, many researchers have tried to overcome the problem by using alternative measures of structural capital. The next section discusses these proposals in the literature in a quest to resolve the issues.

6.3 Earlier Modifications of the Original VAIC Model

The VAIC model pioneered by Pulic (1998) has been quite popular among researchers because of its unique characteristics. For example, Andriessen (2004) argues that the VAIC model uses publicly available data that are audited by reliable resources. Furthermore, Schneider (1998) argues that as sophistication in data collection increases, the reliability of results obtained from those data poses different challenges. Since the VAIC model involves simple financial statement data and its calculations are easy to understand, it provides a perfect basis for comparing IC efficiency across industries (Firer & Williams, 2003). Despite these benefits, the VAIC model has been criticised for several reasons (see section 6.1). In trying to overcome criticisms of the VAIC model, several studies have tried to produce an extended or modified version of the VAIC model. These studies tried different new variables and proxy measures to capture as much information about IC as possible.

Bontis *et al.* (2007), for example, discuss the taxonomy of the VAIC model in detail and propose new variables that can overcome criticisms of the original VAIC model. The basic argument of Bontis *et al.* (2007) relates to the structural capital measure of the VAIC model. The authors divide structural capital into sub-components, customer capital, innovation capital and process capital. Customer capital can be taken as marketing costs, innovation capital can be treated as R&D investment and

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[28] For example, if a firm's value added in any given period is \$10 and if its human capital is \$4 then the SC per Pulic is \$6 (VA-HC). In this case HCE = 10/4 = 2.5. SCE is 6/10 = 0.6. As per equation (6.4), SCE is 1-1/2.5 = 0.6 and HCE as per equation (6.5) is 1/(1-.6) is also 2.5.

[29] In finance, it is generally perceived that when VA increases it means a firm's resources (SC in this case) performed well.

process capital is equal to structural capital minus customer and innovation capital. It is worth mentioning here that rest of the calculations such as VA and efficiency measures are similar to the original VAIC model. Bontis *et al.* (2007) recommend future researchers should use this extended measure to test whether it can increase the reliability of the VAIC model.

Vishnu and Kumar Gupta (2014) propose three new models with two new proxy measures. The new variables include relational capital, which is measured through selling and marketing related expenses. They also replaced the structural capital measure in the original VAIC model with R&D expenses to overcome the criticism of structural capital measurement. The authors argue that since most IC definitions in the literature term R&D as structural capital and marketing costs as relational capital, they use these new proxies. Vishnu and Kumar Gupta (2014) also introduce an intensity model with sales instead of value added to measure the intensity of each variable, namely, human capital, structural capital, relational capital and physical capital. However, their results show that inclusion of the new variables and proxies does not contribute anything new; the ability of the new models to capture IC information is same as the original VAIC model.

Recently, Nimtrakoon and Chase (2015) modified the original VAIC model by introducing a new component, *i.e.,* relational capital, to make the VAIC model more comprehensive. The authors use marketing expenses as a proxy for relational capital. All other calculations, such as VA and efficiency measures, are similar to the original VAIC model. This modified VAIC (m-VAIC) model is then applied to sample firms from ASEAN countries to test the relationship between IC and firm performance but once again no conclusive results are reported.

Vishnu and Kumar Gupta (2014) and Nimtrakoon and Chase (2015), in general, and Bontis *et al.* (2007), in particular, conclude that the VAIC model is not a robust model; alterations and additions can develop a more reliable measure that can calculate the efficiency of IC more accurately. The next section critically discusses the model modifications.

6.3.1 A Critical Overview of the Modifications to the VAIC Model

Several studies have tried to overcome criticisms of the VAIC model by introducing new variables such as innovation capital, process capital and customer or relational capital. These studies have also tried different proxies such as R&D for structural capital and marketing expenses for relational capital. The results from these studies are quite divergent and inconclusive, which further increases the ambiguities about the validity of the VAIC model. For example, Vishnu and Kumar Gupta (2014) report that inclusion of new variables such as relational capital do not show a significant relationship. Ulum *et al.* (2014), however, report that inclusion of relational capital improves the overall results of the VAIC model and hence new variables can be included in the original model.

If we critically look at the criticism of the VAIC model by Ståhle *et al.* (2011) and how previous studies have attempted to overcome this criticism, we note some important differences. First, Ståhle *et al.* (2011) point to the calculation method rather than missing variables. For example, they criticise the way structural capital and its efficiency are measured. The authors clearly point towards the perfect superimposition between human capital and structural capital since human capital is subtracted from VA to obtain structural capital. Similarly, the criticism of structural capital efficiency is legitimate since structural capital is divided by VA to obtain its efficiency[30]. However, studies that try to overcome this criticism focus on only one aspect. These studies (see, for example, Nimtrakoon & Chase (2015), Vishnu & Kumar Gupta (2014)) change the proxy measures of variables or add new variables but use same VA suggested by Pulic (1998). These studies also measure efficiencies in the way suggested by Pulic, *i.e.,* divide structural capital by VA to obtain SCE. This could be one potential reason why modified VAIC model studies produce divergent results. In the next section, we propose some changes to the original VAIC model, through not only a new proxy but also the calculation methods to overcome the criticisms.

6.4 Proposed Adjustments to the VAIC Model in this Current Study

In this section, we propose some adjustments to the original VAIC model to test whether the changes can increase the reliability of VAIC as a comprehensive measure of IC efficiency.

6.4.1 Proposed Changes in the Structural Capital Measure

As criticised by Ståhle *et al.* (2011), the calculations of SC in the VAIC model are problematic. Pulic (1998) subtracts human capital from VA to obtain SC, which is equal to operating profit but has nothing to do with structural capital (Ståhle *et al.*, 2011). Various definitions of IC define IC in different ways. For example, according to Bassi (1997), IC consists of knowledge and its components such as HC, SC and customer capital. Choong (2008) defines IC as sum of investments such as R&D, human costs, copyrights, brand names[31]. These definitions agree there are at least three components of IC, namely, human, structural and relational capital. The structural capital component of IC has been referred to as unique production processes, copyrights, R&D, and sometimes to those infrastructural facilities that help employees make use of their knowledge.

As discussed in Chapter 1, structural capital is the *"sum of unique processes which firms acquire through R&D and then protect in the form of patents and copyrights"*. Under this definition, structural capital refers to investment in R&D, which is the main source of unique processes, and copyrights. Furthermore, R&D investment is the main source of innovation; the literature sometimes refers to SC as *innovation capital* (INVC). We therefore, replace the structural capital measure of the

[30] This has been discussed in detail in section 6.2.1.
[31] A detailed list of different definitions of IC is provided in Table 1.1 in Chapter 1.

VAIC model with R&D investment. Previous studies (Vishnu & Kumar Gupta, 2014; Nimtrakoon & Chase, 2015) that extend the original VAIC model also replace SC with R&D costs. The use of R&D costs as an SC measure has two advantages. First, this investment directly represents SC hence our *Adjusted-VAIC* model includes SC unlike the original VAIC model where SC is the difference between VA and HC. Secondly, the use of R&D investment overcomes the superimposition of VA and HC because R&D is an independent variable in our adjusted A-VAIC model.

6.4.2 Proposed Changes in Structural Capital Efficiency

Pulic (1998) measured SCE as SC divided by VA, which was criticised by Ståhle *et al.* (2011) (see section 6.1.2). It is worth noting here that the previous studies (Vishnu & Kumar Gupta, 2014; Nimtrakoon & Chase, 2015) that modify the original VAIC model, calculate SCE similarly to the original VAIC model hence produce inclusive results. HCE or CEE, which are calculated as VA divided by HC or CE, measures how much value has been added by investing each dollar in HC or CE. SCE is calculated as SC divided by VA, which resembles VA efficiency rather than SCE. One possible reason for the method could be that SC is the difference (superimposition) between VA and HC. Since, in our adjusted VAIC model, INVC (R&D) is an independent variable, we can measure INVC efficiency as follows:

$$INVCE = VA / \text{INVC} ....(6.6)$$

Equation (6.6) measures how much value has been added from each dollar investment in INVC, which is measured as R&D investment. Thus, equation (6.6) is the true representative of INVCE as per general finance principles.

6.4.3 Proposed Changes in the Value Added Measure

As identified in equation (3.3), Pulic (1998) calculates VA by adding labour costs and depreciation and amortization to operating profit. Pulic (1998) argues that since money spent on employees generates long term benefits for the firm, these expenses should be treated as investments. This is why Pulic adds back employee costs to operating profit to obtain net value added. In line with this argument, several authors (Stewart & Ruckdeschel, 1998; Bontis, 1999; Mouritsen *et al.*, 2005) also argue that investment in R&D creates wealth for firms in long run, hence these expenses should be treated as investments rather than expenditure. Further, if employees use their knowledge and skills to create value for the firm then it is SC which enables employees to make use of their skills (see section 6.3.1). Therefore, if employee cost is added back to VA then R&D investment should also be added back since this investment also creates value for firms. Moreover, R&D investment converts knowledge and skill into unique processes that then form the basis of competitive advantage according to RB theory. Therefore, we modify VA equation to add R&D investment to obtain net VA.

$$VA = NI + LC + I + T + DP + R\&D \ldots\ldots (6.7)$$

Equation (6.7) is used to calculate human, structural and physical capital efficiencies in our A-VAIC model.

Finally, our A-VAIC can be written as:

$$A - VAIC = \frac{VA}{HC} + \frac{VA}{INVC} + \frac{VA}{CE} \ldots\ldots (6.8)$$

6.5 Empirical Application of the A-VAIC Model

In this section we apply the proposed A-VAIC to our data set to test if the proposed adjustments overcome previous criticism of the original VAIC model and capture more information on IC resources.

6.5.1 Empirical Models

Our dynamic empirical models with modified variables are:

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 A - VAIC_{it} + \beta_3 \partial X_{it} + T.\lambda + \eta_i + \varepsilon_{it} \ldots\ldots (6.9)$$

$$FP_{it} = \alpha + \beta_1 LFP_{it-1} + \beta_2 HCE_{it} + \beta_3 INVCE_{it} + \beta_4 CEE_{it} + \beta_5 \partial X_{it} + T.\lambda + \eta_i + \varepsilon_{it} \ldots. (6.10)$$

Where A-VAIC is our proposed *adjusted-VAIC* model with INVCE as a new measure for structural capital, ∂ is vector of control variables X and λ is vector of time dummies T. To estimate equations (6.9) and (6.10) we select the Arrelano-Bond *difference GMM* as an estimation method[32]. We select the difference GMM (DGMM) instead of SGMM because DGMM is more appropriate when there are more gaps in the data set (Roodman, 2006). Because of some unavoidable restrictions in our data source (Bloomberg), every firm does not report R&D expenditure; this restriction left us with some gaps in the unbalanced panel data. In this scenario, an extra option in DGMM called *forward orthogonal deviation* is quite useful. This option allows the average future values of the variables to be subtracted from their current values rather than lagged values. In this way the degrees of freedom are preserved whereas they are lost in opposite case because of differencing (Roodman, 2006). We use the two step DGMM with orthogonal deviation. We run the two step instead of one step because the two step produces more efficient estimates and also report the robust Hansen in difference tests that are not available in one step. Because of the unavoidable restrictions in the data source, we were not able to obtain R&D data for frontier markets. Hence, we apply equations (6.9)

[32] General justification of GMM estimator is discussed in detail in Section 5.5.1

and (6.10) to the five developed and five emerging markets in the study. We also run the dynamic OLS to test how many lags of firm performance are significant and find quite similar results to those in Chapter 5, *i.e.,* the first lag will be used as regressor and up to four lags can be used to find optimal instruments.

6.5.2 Empirical Results

Table 6.1 reports the two step DGMM estimation of equations (6.9) and (6.10) with ROA as the dependent variable. In the first model, A-VAIC is used as a comprehensive measure of IC efficiency and in the second model, individual components of A-VAIC namely, HCE, INVCE and CEE, are used as independent variables. Table 6.1 shows A-VAIC is positive and significant with ROA at the 1% level in five markets (Austria, Netherlands, Singapore, China and Turkey) and at the 5% level in three markets (Australia, Sweden and South Africa). This means an increase in IC efficiency exhibits a positive, significant impact on the financial performance of firms in almost all markets in the sample. These results endorse the RB theory that IC resources contribute significantly to firm performance and form the basis for sustainable competitive advantage. The findings from the DGMM estimation are consistent with previous VAIC studies such as Clarke *et al.* (2011) for Australia, Vishnu and Kumar Gupta (2014) for India, Chen *et al.* (2005) for Taiwan and Ting and Lean (2009) for Malaysia.

Model 2 in Table 6.1 reports the results for individual components of the A-VAIC model. One surprising change in the results is that HCE is positive and significant in as many as eight markets in the sample. HCE is significant at the 1% level in Australia, the Netherlands, Sweden, China, Malaysia and South Africa. HCE is significant at the 5% level in Singapore and at the 10% level in Austria. However, HCE is either negatively significant or positively insignificant in our previous results (OLS, FE) including SGMM (see chapter 5). This shows that HCE measurement in the original VAIC model did not accurately depict human capital. This result might be because of the perfect superimposition of SCE and HCE in the original VAIC model. Nonetheless, our results endorse the RD theory that firms utilize their human resources effectively towards value creation for firms. The findings contradict previous studies based on the original VAIC model, such as Firer and Williams (2003) and Mehralian *et al.* (2012), who report no relationship between HCE and firm performance.

The new component in the A-VAIC model namely INVCE is positive and significant in eight markets. INVCE is significant with ROA at the 1% level in Australia, Austria, the Netherlands, Singapore, Sweden, China, South Africa and Turkey. This positive, significant relationship yields two outcomes. First, INVCE is a true measure for structural capital free from perfect superimposition with human capital. This new proxy measure also overcomes the criticisms by Ståhle *et al.* (2011) and Bontis *et al.* (2007) who argue that the structural capital measure in the original VAIC model is not a true measure of structural capital. Secondly, our findings endorse OL theory and, in this regard, Njuguna (2009) states that organizational learning is a process whereby a firm acquires a new wealth of knowledge that can be translated into innovation and can be protected in the form of unique process, models and copyrights. Hence, our findings suggest that firms are able to transform their structural capital resources into innovation, which, in turn, increases the profitability of the firm. Only Russia exhibits a negative significant correlation; this is because very few Russian firms reported R&D values in Bloomberg, hence our data set for Russian firms, in terms of R&D, is very small. Table 6.1 shows the CEE results are similar to those in reported Chapter 5 as well as in our OLS and FE estimation. These findings validate the overall argument of the importance of physical capital for value creation that cannot be eliminated.

Table 6.1 The Dynamic Panel-Data Estimation, Twostep Difference GMM Results with ROA as the Dependent Variable

	Model 1		Model 2			
	L.ROA	A-VAIC	L.ROA	HCE	INVCE	CEE
			Developed Economies			
Australia	0.287**	0.278**	0.218*	0.296*	0.173*	0.878*
	(0.024)	(0.012)	(0.000)	(0.006)	(0.000)	(0.000)
Austria	-0.047	0.747*	0.444***	0.851***	0.949*	-1.142
	(0.682)	(0.000)	(0.054)	(0.068)	(0.008)	(0.156)
Netherlands	0.018	0.226*	-0.114	3.196*	0.276*	-0.660**
	(0.572)	(0.007)	(0.629)	(0.003)	(0.000)	(0.017)
Singapore	0.631*	0.569*	0.257*	0.162**	0.174*	1.303*
	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)
Sweden	-0.013	0.044**	0.229*	0.315*	0.106*	0.488*
	(0.631)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)
			Emerging Economies			
China	0.587*	0.365*	0.231*	0.159*	0.161*	0.561*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Malaysia	0.323*	0.021	0.322*	0.497*	0.045	0.932*
	(0.003)	(0.807)	(0.005)	(0.005)	(0.649)	(0.000)
Russia	0.103	0.039	-0.503	-1.159	-0.300**	2.041**
	(0.757)	(0.857)	(0.131)	(0.414)	(0.046)	(0.041)
South Africa	0.289*	0.050**	0.121*	0.466*	0.112*	1.070*
	(0.000)	(0.018)	(0.000)	(0.000)	(0.003)	(0.000)
Turkey	0.152*	0.374*	0.047*	-0.035	0.041*	0.520*
	(0.000)	(0.000)	(0.000)	(0.196)	(0.000)	(0.000)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10, respectively; p-values are in parentheses; L.ROA is one year lagged ROA. Control variables and time dummies were included in all specifications.

Source: Author's calculations

We also apply robustness checks by replacing ROA with ROE as the performance measure; Table 6.2 reports the results. Table 6.2 results are quite similar to those reported in Table 6.1. With ROA as the dependent variable, IC efficiency in terms of A-VAIC is once again positive and significant at the 1% level with ROE in seven markets (Austria, the Netherlands, Singapore, Sweden, China, South Africa and Turkey). These findings again endorse RB theory that IC resources contribute significantly towards a firm's performance. The findings also demonstrate the accuracy of the A-VAIC model in measuring the efficiency of IC. Individual component analysis of A-VAIC produces similar results to those from ROA (see Table 6.1). The results in Table 6.2 show that HCE is positive and significantly related to ROE as the dependent variable in eight markets (at the 1% level in Australia, the Netherlands, Sweden, China, Malaysia and South Africa;, at the 5% level in Turkey and at the 10% level in Austria). These findings endorse RD theory that human capital is a valuable resource and firms should use this resource effectively to create more value. The findings reject the argument by Firer and Williams (2003) that firms treat spending on employees as expenditure and hence is not important for value creation. The findings suggest that spending on employees should be treated as investment because it contributes significantly towards the financial performance of firms.

Our new proxy measure for structural capital, *i.e.,* INVCE, is also positive and significantly related to ROE in seven markets (see Table 6.2). INVCE is significant at the 1% level in Austria and Singapore, at the 5% level in the Netherlands, Sweden, China and South Africa and at the 10% level in Australia. These findings again endorse OL theory that firms acquire and utilize structural capital resources efficiently and that they contribute significantly towards the financial performance of the firm. The findings also postulate that INVCE is a more accurate measure of structural capital than Pulic's VAIC model.

Table 6.2 The Dynamic Panel-Data Estimation, Twostep Difference GMM Results with a Robustness Check with ROE

	Model 1		Model 2			
	L.ROE	A-VAIC	L.ROE	HCE	INVCE	CEE
			Developed Economies			
Australia	0.504*	0.175	0.162*	0.214*	0.072***	0.843*
	(0.002)	(0.222)	(0.000)	(0.000)	(0.052)	(0.000)
Austria	-0.112	0.586*	0.410**	0.787***	0.804*	-0.184
	(0.487)	(0.003)	(0.010)	(0.074)	(0.003)	(0.671)
Netherlands	0.068**	0.253*	-0.598*	4.464*	0.183**	-0.740***
	(0.031)	(0.002)	(0.001)	(0.000)	(0.048)	(0.071)
Singapore	0.770*	0.380*	0.201*	0.009	0.240*	1.377*
	(0.000)	(0.000)	(0.001)	(0.939)	(0.000)	(0.000)
Sweden	0.130*	0.112*	0.094*	0.286*	0.074**	0.602*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.025)	(0.000)
			Emerging Economies			
China	0.578*	0.353*	0.211*	0.234*	0.111**	0.732*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.042)	(0.000)
Malaysia	0.436*	0.288	0.355*	0.645*	0.064	0.971*
	(0.000)	(0.202)	(0.004)	(0.001)	(0.407)	(0.000)
Russia	0.304***	0.027	1.098	1.071	0.251	-1.526
	(0.057)	(0.915)	(0.176)	(0.441)	(0.366)	(0.674)
South Africa	0.382*	0.177*	0.105*	0.486*	0.073**	1.233*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)
Turkey	0.115*	0.210*	-0.003	0.067**	0.000	0.652*
	(0.000)	(0.005)	(0.695)	(0.020)	(0.900)	(0.000)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10 respectively; p-values are in parentheses; L.ROE is one year lagged ROE. Control variables and time dummies were included in all specifications.

Source: Author's calculations

6.5.3 Specification Tests of DGMM

The reliability of GMM (Difference and/or System) depends on some specification tests[33] (Roodman, 2006). The specification test results are shown in Tables 6.3 and 6.4 for ROA and ROE, respectively. As argued by Arellano and Bond (1991), the GMM estimator requires first-order autocorrelation but not second-order. They also suggest AR1 and AR2 tests for first and second-order autocorrelation in

[33] Details of these specification tests can be found in Section 5.6

GMM. In Tables 6.3 and 6.4, the *p-values* of AR1 reject the null hypothesis whereas the *p-values* of AR2 cannot reject the null hypothesis in almost all markets. Thus there is first-order autocorrelation in our data but no second-order autocorrelation. These results allow GMM to use lagged values of variables as instruments.

Roodman (2006) suggests that one should check the validity of instruments using the Hansen J. Test for over-identification restrictions and Difference-in-Hansen Test. Tables 6.3 and 6.4 show the *p-values* of both the Hansen J. Test and the Difference-in-Hansen Test are well above any conventional significance level, which means we do not reject the null hypotheses. This implies that the instruments used in DGMM are correctly identified and are valid instruments. Roodman (2006) further argues that one should always report the number of instruments since it can also be used to check for the validity of the instruments. The rule of thumb is that the number of instruments should always be fewer than the number of observations. The number of instruments is fewer than the number of observations in all the markets, which validates the argument (see Tables 6.3 and 6.4). Hence, the specification tests validate the results of the DGMM estimations reported in Tables 6.1 and 6.2.

Table 6.3 The Dynamic Panel-Data Estimation, Diagnostic Tests with ROA as the Dependent Variable

	Model 1 (A-VAIC)						Model 2 (HCE,INVCE,CEE)					
	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id	Han.J. Diff	No.INS	Obs.
						Developed Economies						
Australia	0.057	0.386	0.845	0.607	34	322	0.024	0.547	0.649	0.623	60	322
Austria	0.044	0.382	0.289	0.565	24	127	0.049	0.586	0.974	0.811	36	127
Netherlands	0.090	0.209	0.981	0.865	38	119	0.064	0.247	0.946	0.487	36	119
Singapore	0.016	0.811	0.838	0.810	24	211	0.011	0.235	0.840	0.648	68	211
Sweden	0.030	0.108	0.508	0.385	50	259	0.036	0.277	0.847	0.882	60	259
						Emerging Economies						
China	0.000	0.935	0.068	0.100	38	2002	0.000	0.071	0.097	0.087	86	2002
Malaysia	0.008	0.370	0.230	0.511	34	257	0.005	0.417	0.180	0.869	36	257
Russia	0.310	0.251	0.990	0.976	37	47	0.240	0.939	0.999	0.955	36	47
South Africa	0.019	0.838	0.608	0.345	38	173	0.071	0.888	0.900	0.990	92	173
Turkey	0.002	0.591	0.539	0.563	39	232	0.002	0.501	0.454	0.287	69	232

Note: This table presents *p-values* (except for No INS and Obs.) of difference GMM tests of the specification. AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively. Han.J,O.Id is Hansen J. Test for over identification of instruments. Han.J.Diff is the Difference-in-Hansen Test for exogeneity of instruments. No.INS is number of instruments used in each specification and Obs is number of observations.

Source: Author’s calculations

Table 6.4 The Dynamic Panel-Data Estimation, Diagnostic Tests with ROE as the Dependent Variable ROE

	Model 1 (A-VAIC)						Model 2 (HCE,INVCE,CEE)					
	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id	Han.J. Diff	No.INS	Obs.
						Developed Economies						
Australia	0.030	0.472	0.854	0.591	34	316	0.039	0.693	0.633	0.861	68	316
Austria	0.028	0.285	0.144	0.307	24	124	0.024	0.843	0.963	0.866	36	124
Netherlands	0.050	0.085	0.969	0.565	38	119	0.160	0.696	0.975	0.661	36	119
Singapore	0.013	0.608	0.805	0.906	24	211	0.020	0.601	0.377	0.336	40	211
Sweden	0.034	0.069	0.297	0.207	50	254	0.034	0.115	0.993	0.995	92	254
						Emerging Economies						
China	0.000	0.324	0.403	0.131	34	1998	0.000	0.402	0.382	0.547	40	1998
Malaysia	0.035	0.900	0.538	0.362	22	256	0.013	0.651	0.290	0.101	36	256
Russia	0.000	0.192	0.917	0.769	24	43	0.010	0.785	0.990	0.997	31	43
South Africa	0.005	0.807	0.842	0.664	50	173	0.080	0.863	0.396	0.649	40	173
Turkey	0.003	0.697	0.353	0.213	39	232	0.001	0.581	0.393	0.358	69	232

Note: This table *presents p-values* (except for No INS and Obs.) of difference GMM tests of the specification; AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively; Han.J,O.Id is the Hansen J. Test for over identification of instruments' Han.J.Diff is the Difference-in-Hansen Test for exogeneity of instruments; No.INS is number of instruments used in each specification and Obs is number of observations.

Source: Author's calculations

6.6 Discussion of the A-VAIC Results

The VAIC model of Pulic (1998; 2004) has earned great popularity among researchers and companies for measuring the efficiency of IC. This popularity was partly because of several benefits of the VAIC model. For example, the model uses publicly available audited information which increases the reliability of the results. Another attribute of the VAIC model is that its calculations are easy to understand and the results are easy to interpret. Criticism of the VAIC model started with Firer and Williams (2003) and Bontis *et al.* (2007). Following these, the VAIC model was also criticised by Ståhle *et al.* (2011), among others, for its reliability. The major criticism by these authors concerns the structural capital measure of the VAIC model. Perfect superimposition of HC and SC has also been a point of critical focus[34].

Attempts have been made to modify the VAIC model and its measures to increase its reliability. Vishnu and Kumar Gupta (2014), for example, modified the structural capital measure of the VAIC model and introduce a relational capital element into the VAIC model. In a recent study by Nimtrakoon and Chase (2015), the authors add one more variable, relational capital, which covers the marketing expenses. Similar changes have previously been made by Bontis *et al.* (2007). A common point in these studies is that they either add extra variables, such as relational capital (Vishnu & Kumar Gupta, 2014) and/or they change the proxy measure of structural capital (such as R&D costs). These studies merely take into account problematic calculations such as VA and SCE. As argued by Ståhle *et al.* (2011), the SCE measure is problematic and can produce misleading results (see section 6.1.2). Pulic (1998) argued that spending on employees is investment hence should be added back into VA. Previous researchers treat R&D as structural capital but did not add back into VA hence ultimately do not consider spending on R&D as investment.

This current study addresses the criticisms in a more systematic way. We treat R&D spending as investment and add them back to VA. It is documented in the literature that R&D investment produces long-term benefits for the firms[35]. We also replace the old measure of SC with INVC (R&D as a proxy) in A-VAIC, which makes it independent of HC. This modification also eliminates the synergistic effect in the original VAIC model that has been criticised. Furthermore, we calculate INVCE by dividing VA by INVC to make its measurement more logical.

Following these modifications, the results in Tables 6.1 and 6.2 are clear evidence of the usefulness of the changes. One main indication comes from the significance of human capital that was insignificant in previous studies and/or before these modifications. The robustness of our proposed A-VAIC with ROE as dependent variable also shows the reliability of the new IC efficiency measure,

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[34] Details can be found in Section 6.1.
[35] Details can be found in Section 6.3

i.e., A-VAIC. Previous studies in which there were attempts to modify the VAIC model are limited to small samples or based on one market whereas this current study provides evidence from developed and emerging markets. The vast scope of our study provides evidence in favour of the proposed A-VAIC. We also use a more advanced estimation method, *i.e.,* dynamic panel data estimator (GMM) which overcomes several econometric problems such as heteroscedasticity and endogeneity, and produces more reliable results.

6.7 Chapter Summary

Despite vast use of the VAIC model by researchers and firms to measure IC efficiency, there are some criticisms of the model. Ståhle *et al.* (2011), for example, criticise the taxonomy of the VAIC model in general and its structural measurements, in particular. Our critical discussion reveals how previous studies document divergent results including after certain changes in the original VAIC model. Our study proposes some adjustments to the VAIC model that are justified on the basis of theoretical and empirical evidence.

Since the literature classifies structural capital as R&D investment, we replace the structural capital measure of the VAIC model with R&D investment (INVC). This adjustment serves two purposes. First, it eliminates the perfect interrelationship between HC and SC. The results from the application of the A-VAIC model show that, after replacing the SC measure with INVC, the sign and significance of the relationship between HCE and firm performance changed significantly. Secondly, this change overcomes the general criticism that SCE of the VAIC model is not a true representative of structural capital. Therefore, the literature suggests that R&D is a better proxy for SCE, INVCE in this study.

Similarly, the calculation of INVC efficiency and VA have been revised in accordance with basic financial rules. R&D spending has been added back into VA since we argue that spending on R&D should be treated as an investment because of its long-term contribution towards a firm's performance and competitive advantage. The DGMM estimator is then applied to measure the relationship between A-VAIC and its components and firm performance. Because of the unavailability of R&D data for frontier markets, the sample consists of developed and emerging markets. The results reveal that A-VAIC is positive and significant (at the 1% level) in five markets and at the 5% level in three markets. These results from developed as well as emerging markets show that the A-VAIC is a more reliable measure of IC efficiency. HCE, which is negative and insignificant in Chapters 4 and 5, where the original VAIC model is used, is now positive and significant (at 5% or better) in eight markets. We argue that the mixed results relating to HCE and firm performance in the literature as well as in Chapters 4 and 5 of this study are because of the superimposition between HCE and SCE in the original VAIC model. Once this superimposition has been eliminated by replacing the SCE measure with INVCE, the results on HCE and firm performance change.

The new measure*, i.e*., INVCE, is positive and significantly (at the 1% level) correlated with ROA in eight markets. The insignificant relationship between INVCE and firm performance in Russia is because of limited data. The robustness check with ROE as a measure of the firm performance yields similar results. A-VAIC and its components HCE, INVCE and CEE are positive and significant in most markets in this study. The specification tests of DGMM, such as autocorrelation and instrument validity tests, validate the results of our estimation. The results with A-VAIC as an IC efficiency measure endorse IC related theories namely the RB, RD and OL theories, which implies that IC resources contribute significantly towards the financial performance of firms. Moreover, modern firms can use IC resources to build a sustainable competitive advantage as argued in the RB theory.

Chapter 7

Conclusions and Policy Implications

7.1 Introduction

Intellectual capital has been among the most investigated strand of accounting and corporate finance fields over the last couple of decades. The evolution of a specific journal "*Journal of Intellectual Capital*" and enormous theoretical and empirical studies published in various other journals such as "*Measuring Business Excellence*", are evidence of this emerging research field. The importance of IC increased especially after the 1997 Asian financial crisis and the great financial crisis of 2008. The reason behind the pivotal role of IC during financial turmoil is that when firms are financially hampered during the crisis, they look for other means of survival such as the use of intellectual resources (Sumedrea, 2013). The purpose of this study is to investigate the efficiency of IC and its impact on the financial performance of firms in different economies, *i.e.*, developed, emerging and frontier markets.

The rest of this chapter is structured as follows: Section 7.1 discusses the overall findings of the research; section 7.2 presents the policy implications of the research results. Section 7.3 discusses the contributions of the study and section 7.4 presents the limitations of this study and makes recommendations for future research.

7.2 Summary of the Major Findings

Despite the vital role of IC in firm performance, existing studies on IC and firm performance have produced quite divergent results (see Table 7.1). These mixed results are attributed to different facts such as the underlying methods to measure the efficiency of IC. The study sample and the economic development levels of the countries in the study have also been presented as reasons behind the mixed results.

Most existing studies investigating the relationship between IC and firm performance have applied static estimators such as OLS and fixed-effects (see Table 7.1), which could be one potential reason behind the divergence. Based on this divergence, the purpose of this study is to investigate the relationship between IC and firm performance with some unique attributes.

Table 7.1 Selected Studies on IC and Firm Performance

Authors	D. Variables	I. Variables	Methodology	Relationship	Country
Daniel Ze´ghal (2010)	OI/S, ROA, M/B	VAIC, CE, HC, SC	OLS	Positive	UK
Stahle et al. (2011)	MV, ROE, ROA	VAIC, HC, CE, SC	OLS	None	Finland
Clark et al. (2011)	ROA, ROE, RG, EP	HC, SC, CE	OLS	Positive	Australia
Chen et al. (2005)	ROA, ROE, RG, EP	VAIC,HC, SC, CE	OLS	Positive	Taiwan
Ting (2009)	ROA	VAIC, HCE, CE, SC	OLS	Positive	Malaysia
HSU (2012)	ROA	VAIC, HC, SC, RC	Bayesian Regression	Positive	Taiwan
Berzkalne (2014)	Tobin Q	VAIC, HC,SC,CE	OLS	Positive	Latvia, Lithuania, Estonia
Tan et al. (2007)	ROE, EPS, ASR	VAIC, HC,CE,SC	PLS	Positive	Singapore
Firer & Williams (2003)	ROA, ATO, M/B	VAIC, HC,CE,SC	OLS	None	South Africa
Joshi (2013)	ROA	VAIC, HC,CE,SC	OLS	Mixed	Australia
Gigante (2013)	ROA,ROE,M/B	VAIC, HC,CE,SC	OLS	Positive	Czech Republic, Denmark, Finland, Germany, Italy, Norway, Poland, Spain, Sweden
Maditinos et al. (2011)	ROA,ROE,M/B	VAIC, HC,CE,SC	OLS	Mixed	Greece
Bharathi Kamath (2008)	ROA,ATO,M/B	VAIC, HC,CE,SC	OLS	Positive	India

Source: Author's compilation

This study employs a large sample of firms for a relatively longer time of 10 years to investigate the accumulation of IC and its efficiency[36]. This study focuses on different economic development levels, *i.e.,* developed, emerging and frontier markets, to compare the efficiency of IC across different markets. This study also investigates whether the relationship between IC and firm performance is dynamic[37] and should be measured using DPD estimators. The VAIC model used to measure the efficiency of IC has been criticized in the literature[38], especially its structural capital measure. Thus, we make some important adjustments to the VAIC model and introduce the A-VAIC to test

[36] This gap was initially identified by Firer and Williams (2003) who argue that accumulation of intellectual resources takes time hence should be studied over a longer time of five to ten years.
[37] If the underlying nature of the relationship between IC and firm performance is dynamic, then it means most previous studies using static OLS or fixed-effects produced biased, inconsistent results (Baltagi, 2008).
[38] See among others Vishnu and Kumar Gupta (2014) and Ståhle *et al.* (2011).

developed and emerging markets. The major findings of the study are presented in the following sections.

7.2.1 Preliminary Findings

The descriptive analysis shows that the mean IC efficiency (VAIC) varies across different economies. The mean IC efficiency is highest for developed markets (7.90) followed by frontier markets (7.26) and emerging markets (7.10). It is worth mentioning here that the mean scores in frontier markets are high particularly because of the extraordinary value for Saudi Arabia (11.36); the mean is 6.24 for the other frontier markets. This preliminary analysis shows that economically developed markets are more efficient in accumulating and utilizing IC. The mean IC efficiency scores are consistent with those reported by Joshi *et al.* (2013) for the Australian financial sector (8.82) but the scores are higher than those reported by Chen *et al.* (2005) for Taiwan (5.49). The mean VAIC scores in our study (7.90) are generally higher than for European countries reported by Gigante (2013) (Czech Republic, Denmark, Finland, Germany, Italy, Norway, Poland, Spain and Sweden) and, in particular, the VAIC scores for Sweden (8.57) in this study are much higher than those for Sweden (3.97) in Gigante's study. These mean IC efficiency scores, however, are slightly lower than those reported by El-Bannany (2008) for UK banks (10.80).

The individual components of the VAIC model show that the mean HCE is again highest for developed markets (6.66) followed by emerging markets (6.20) and lowest for frontier markets (5.09). This means that firms in developed markets are more efficient in utilizing human capital than their counterparts in emerging and frontier markets. Emerging markets exhibit the highest mean SCE (0.61) followed by frontier markets (0.61) and developed markets (0.51). The mean CEE efficiency for frontier markets is highest (1.55) and lowest for emerging markets (.0.33) which is consistent with the general argument by Firer and Williams (2003) that firms in most under-developed markets still rely heavily on physical capital. The mean IC efficiency trend over 10 years (2005-2014) shows that IC efficiency has gone down, especially after the financial crisis of 2008 in almost all markets in the study but the trend either flattens or reverses more recently. One possible reason behind this decreasing trend is that the firms cut their investment in IC resources after the financial crisis but started to re-invest in recent years, 2013 and 2014.

7.2.2 Empirical Findings

This section discusses the empirical findings of the relationship between IC and firm performance. Before examining this relationship based on panel data, this study applied some basic diagnostic tests to eliminate spurious regression problems. We implemented the panel data unit root test, *i.e.,* the Fisher-Type *p* test, because of its unique characteristics discussed in Chapter 4. The results in

Table 4.4 show that there is no unit root problem in the data set, which means that the mean and variance does not depend on time, hence the application of CLRM can produce meaningful results (Gujarati, 2012). Next, we apply the Pearson correlation to test for correlation among variables. The results in Appendix Tables A1 to A3 show that there is a significant correlation among the variables, which prompts further empirical investigation. If the correlation among variables is more than 0.80, then multicollinearity exits (Gujarati, 2012), which violates the basic assumption of CLRM. The results indicate that no correlations exceeds 0.80, which means there is no multicollinearity in the dataset. The next sections discusses the findings of the static and dynamic estimations.

7.2.2.1 IC and Firm Performance – Static OLS and Fixed-Effects Estimation

In the first stage, we apply static OLS and the FE estimator to measure the relationship between IC and firm performance. Table 7.2 summarizes the results from these estimators. The results show that there is a positive, significant (at 1%) relationship between VAIC and ROA in all 15 markets in our study. These results endorse the RB theory that IC resources are vital for value creation in firms. Our findings are consistent with previous similar studies that use static estimators such as OLS and fixed effects (Ting & Lean, 2009; Clarke *et al.*, 2011; Vishnu & Kumar Gupta, 2014). Human capital, however, produces inclusive results, *i.e.*, either an insignificant or negatively significant relationship is observed with ROA. These results do not endorse RD theory which means that HC is not being utilized efficiently in most markets. The negative significant relationship between HCE and ROA shows that owners still treat investment in personnel as expenses (Frederickson *et al.*, 2010).

SCE and CEE, however, are positive and significant (at 5% or less) in all 15 markets in OLS as well as fixed-effects estimations. This significance of SCE confidently endorses LO theory which means that firms in almost all types of market can utilize their structural capital resources efficiently to bring innovation in their products and services. The significant relationship between CEE and ROA in OLS, as well as the fixed-effects model, is consistent with the general argument that physical capital is still a major contributor towards firm performance. We test for robustness by applying ROE, ATO and P/B as other performance measures; Table 4.6 and Appendix Tables B1, B2, C1, C2 and C3 present the results. ROE as a performance measure produces quite similar results to ROA but no significant relationship is observed between IC efficiency and P/B. Our results again are consistent with previous studies (Chan, 2009b; Pal & Soriya, 2012; Gigante, 2013) that report a significant relationship between IC and ROA or ROE but no relationship between IC and M/B.

Table 7.2 A Summary of the Results from OLS and Fixed-Effects Estimations

Dependent Variable ROA	Static OLS				Fixed-Effects			
	VAIC	HCE	SCE	CEE	VAIC	HCE	SCE	CEE
Australia	(+)*	(+)	(+)*	(+)*	(+)*	(+)*	(+)*	(+)*
Austria	(+)*	(-)	(+)*	(+)*	(+)*	(-)***	(+)*	(+)*
Netherlands	(+)*	(-)	(+)*	(+)*	(+)	(-)**	(+)*	(+)*
Singapore	(+)*	(+)*	(+)*	(+)*	(+)*	(+)**	(+)*	(+)*
Sweden	(+)*	(+)*	(+)*	(+)*	(+)*	(-)	(+)*	(+)*
China	(+)*	(-)	(+)*	(+)*	(+)*	(+)*	(+)*	(+)*
Malaysia	(+)*	(+)	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Russia	(+)*	(-)	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
South Africa	(+)*	(+)	(+)*	(+)*	(+)*	(-)**	(+)*	(+)*
Turkey	(+)*	(+)*	(+)*	(+)*	(+)*	(+)***	(+)*	(+)*
Argentina	(+)*	(+)	(+)*	(+)*	(+)*	(-)	(+)*	(+)*
Nigeria	(+)*	(-)*	(+)*	(+)*	(+)*	(-)**	(+)	(+)**
Pakistan	(+)*	(+)*	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Saudi Arabia	(+)*	(+)*	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Ukraine	(+)*	(+)***	(+)*	(+)*	(+)*	(+)	(+)*	(+)*

Note: (+) and (-) represent positive and negative relationships; *, ** and *** indicate significance at 0.01, 0.05 and 0.10, respectively.
Source: Author's calculations

We then apply some advanced diagnostic tests such as the Breusch-Pagan Test to test for heteroscedasticity and the Woolridge (2002) Test for autocorrelation (see Table 4.8 and Appendix Table D). The results provide sufficient evidence for the presence of both heteroscedasticity and autocorrelation. Though both these problems are resolvable even with OLS and fixed-effects estimators but at this point, we investigate another potential econometric problem, *i.e.*, the presence of endogeneity (mainly because of simultaneity and unobserved heterogeneity). The next section summarizes the findings on the dynamic nature of the relationship between IC and firm performance.

7.2.2.2 IC and Firm Performance – Dynamic Panel Data Estimation

One objective of this study is to test if the relationship between IC and firm performance is dynamic. For this purpose, we first provide theoretical evidence in support of the argument that the IC and firm performance relationship is dynamic. Section 5.2 of Chapter 5 describes the potential existence of simultaneity. Based on previous studies (Mulkay *et al.*, 2001; Harmantzis & Tanguturi, 2005; Brown *et al.*, 2009; Murthy & Mouritsen, 2011; Becker, 2013), we explain how investment in IC resources depends on past firm performance. These studies provide sufficient evidence that better firm performance leads to more investment in IC resources, including the human and structural capital.

For empirical evidence, following Wintoki *et al.* (2012), we apply both dynamic OLS and Wooldridge (2002) strict exogeneity tests. The dynamic OLS results in Table 5.1 provide clear evidence that a firm's past performance acts as a regressor. This can be observed from the increase in adjusted R-squared from the static OLS to dynamic OLS and also from the fact that the coefficients on the lagged dependent variable are significantly different from zero in all 15 markets in the study. The Wooldridge Test results in Table 5.2 provide sufficient evidence that the null hypotheses can be rejected (at 10% or less) in all markets. This implies that future values of the independent variables (IC) are correlated with current or past values of the dependent variable (firm performance), which is endogeneity. Another important point is to check how many lags of firm performance are significant. We ran the OLS of current firm performance on past firm performance controlling for IC and control variables. Table 5.3 reports the results. We first include two lags and notice that the first two lags are highly significant. In the next regression, we include the third and fourth lags (dropped lags 1&2) and note that only the third lag is significant. Finally, we include all four lags and the results[39] show that, in most cases only the first lag is significant. This shows that the effect of older lags is subsumed in the first lag hence we include only the first lag of IC as a regressor and the other lags (2-4) may be used as instruments.

Next, we apply the two-step SGMM to investigate the dynamic relationship between IC and firm performance in the presence of heteroscedasticity, autocorrelation and endogeneity problems. Table 7.3 summarizes the results from the DPD estimation[40]. We reconfirm a significant (at 5% or less) positive relationship between VAIC and ROA in the SGMM estimation. This implies that IC efficiency has a positive impact on firm performance. Our findings again endorse RB theory that intangible resources are a great source of wealth creation and competitive advantage for firms in modern knowledge-based economies. This also confirms the argument by Kolachi and Shah (2013) that IC is important for all types of firm (big or small) in all types of market (developed or underdeveloped). Zéghal and Maaloul (2010) state that firms can yield extra returns and build competitive advantage from the effective use of their strategic resources such as IC assets. Our findings are consistent with Zéghal and Maaloul (2010) argument, which means when IC efficiency increases, firm performance (ROA) also increases.

[39] Results are not reported to save space but are available upon request.
[40] The detailed results are presented in Tables 5.4 & 5.5 and Appendix Tables E1 & E2.

Table 7.3 A Summary of the Original VAIC Model Results from the Two-Step Robust System GMM

	Dependent Variable ROA				Dependent Variable ROE			
	VAIC	HCE	SCE	CEE	VAIC	HCE	SCE	CEE
Australia	(+)*	(+)	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Austria	(+)**	(-)	(+)*	(+)*	(+)***	(-)**	(+)*	(+)*
Netherlands	(+)	(-)	(+)*	(+)*	(+)	(-)	(+)*	(+)*
Singapore	(+)*	(+)	(+)*	(+)*	(+)*	(-)	(+)*	(+)*
Sweden	(+)*	(+)**	(+)*	(+)*	(+)**	(+)	(+)*	(+)*
China	(+)*	(-)**	(+)*	(+)*	(+)*	(-)**	(+)*	(+)*
Malaysia	(+)*	(-)	(+)*	(+)*	(+)*	(-)	(+)*	(+)*
Russia	(+)*	(-)	(+)**	(+)*	(+)**	(-)	(+)*	(+)*
South Africa	(+)**	(-)	(+)*	(+)*	(+)**	(-)	(+)*	(+)*
Turkey	(+)*	(+)*	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Argentina	(+)	(-)	(+)*	(+)*	(+)****	(-)	(+)*	(+)*
Nigeria	(+)*	(-)	(+)*	(+)*	(-)**	(-)***	(+)	(-)**
Pakistan	(+)*	(-)	(+)*	(+)*	(+)*	(-)**	(+)*	(+)*
Saudi Arabia	(+)*	(+)*	(+)**	(+)*	(+)*	(+)	(+)*	(+)*
Ukraine	(+)*	(+)	(+)*	(+)*	(+)*	(+)	(+)*	(+)*

Note: (+) and (-) represent the positive and negative relationship; *, ** and *** indicate significance at 0.01, 0.05 and 0.10, respectively.
Source: Author's calculations

HCE shows an insignificant relationship with ROA in most markets which means that the results cannot endorse RD theory. SCE and CEE, however, are positive and significant (at 5% or less) in almost all 15 markets which means that the results endorse OL theory. Our robustness check with ROE as the firm performance measure produce consistent results where VAIC, SCE and CEE are significant (at 10% or less) in most markets. HCE is again insignificant. Our findings of SGMM estimation are consistent with previous studies (Clarke *et al.*, 2011; Kai *et al.*, 2011; Vishnu & Kumar Gupta, 2014) where VAIC, SCE and CEE are positive and significantly related to firm performance in terms of ROE. Our diagnostic tests of SGMM verify the reliability of the results and that SGMM estimator is the most appropriate estimator to investigate the dynamic relationship between IC and firm performance. We also investigate the relationship between IC and firm performance during the 2008 financial crisis. The interaction terms between the dummy variable for 2008 and IC efficiency show the insignificant relationship between IC and firm performance during financial turmoil, which means IC efficiency remained unchanged during the 2008 financial crisis.

7.2.2.3 Adjustments to VAIC Model (A-VAIC)

The VAIC model has been criticized in the literature[41]. We, therefore, make the following adjustments to the original VAIC model[42]. First, we replace the structural capital measure with *innovation capital* (R&D as a proxy measure), since investment in R&D is considered a major source of structural capital. This change makes INVCE independent of HCE or eliminates superimposition between SCE and HCE as in the original VAIC model. Second, as R&D investment is a source of innovation and long-term competitive advantage, hence we treat R&D spending as investment and add back to operating profit to obtain value added just like personnel cost. Third, we change the calculation technique of the INVCE measure to similar to HCE or CEE to make it more practical. We rename the original VAIC model A-VAIC after making these changes. These adjustments present a more relevant measure of IC efficiency.

We then apply the two-step difference GMM to equations (6.9) and (6.10) to measure the relationship between A-VAIC and its components, *i.e.,* HCE, INVCE, CEE and firm performance. We run the difference GMM instead of SGMM because DGMM is more appropriate since there are missing values in the data set. We could get R&D data only for developed and emerging markets hence the sample is now 10 markets (emerging and developed). A summary of the results is presented in Table 7.4. A-VAIC is positive and significantly (at 5% or less) related to ROA in eight markets. This implies that an increase in IC efficiency has a positive, significant impact on a firm's financial performance. These findings endorse RB theory that IC resources are vital for value creation firms.

We use equation (6.10) to investigate the relationship between the individual components of A-VAIC, *i.e.,* HCE, INVCE and CEE, and firm performance. The results in Table 7.4 indicate that HCE is now positive and significant (at 5% or less) in eight markets. This implies that an increase in HCE leads to better firm performance. These findings endorse the RD theory that firms in developed and emerging markets utilize their human resources efficiently to increase value. It is worth mentioning that HCE was either negatively significant or positively insignificant in previous results (OLS, FE) including SGMM. This shows that the HCE measure in the original VAIC model did not accurately depict human capital. This may have been because of the perfect superimposition of SCE and HCE in the original VAIC model.

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[41] See, for example, Ståhle *et al.* (2011), Vishnu and Kumar Gupta (2014) and Bontis *et al.* (2007).

[42] For details see sections 6.1, 6.2 and 6.3 of Chapter 6.

Table 7.4 A Summary of the A-VAIC Model Results from the Robust Two-Step Difference GMM

	Dependent Variable ROA				Dependent Variable ROE			
	A-VAIC	HCE	INVCE	CEE	A-VAIC	HCE	INVCE	CEE
Australia	(+)**	(+)*	(+)*	(+)*	(+)	(+)*	(+)***	(+)*
Austria	(+)*	(+)**	(+)*	(-)	(+)***	(+)***	(+)*	(-)
Netherlands	(+)*	(+)*	(+)*	(+)**	(+)	(+)*	(+)**	(-)***
Singapore	(+)*	(+)**	(+)*	(+)*	(+)*	(+)	(+)*	(+)*
Sweden	(+)**	(+)*	(+)*	(+)*	(+)**	(+)*	(+)**	(+)*
China	(+)*	(+)*	(+)*	(+)*	(+)*	(+)*	(+)**	(+)*
Malaysia	(+)	(+)*	(+)	(+)*	(+)	(+)*	(+)	(+)*
Russia	(+)	(-)	(-)**	(+)**	(+)	(+)	(+)	(-)
South Africa	(+)*	(+)*	(+)*	(+)*	(+)*	(+)*	(+)**	(+)*
Turkey	(+)*	(-)	(+)*	(+)*	(+)*	(+)**	(+)	(+)*

Note: (+) and (-) represent the positive and negative relationship; *, ** and *** indicate significance at 0.01, 0.05 and 0.10, respectively.
Source: Author's calculations

Our new component in A-VAIC model, INVCE, is positive and significantly (at 1%) related to ROA in nine markets. This implies that an increase in INVCE affects firm performance significantly. This positive, significant relationship yields two outcomes. First, our new measure, *i.e.,* INVCE, is a true measure of structural capital that is free from perfect superimposition with human capital. Second, this new proxy also overcomes the criticism by Bontis *et al.* (2007) and Ståhle *et al.* (2011) about the structural capital measure in the original VAIC model. This finding endorses the LO theory that firms can acquire knowledge and translate it into innovation. CEE is positive and significantly (at 5% or less) related to ROA in nine markets, which implies that physical capital plays a vital role in defining firm performance.

We then apply ROE as a performance measure to check for the robustness of the results. Table 7.4 results, based on ROE as the dependent variable, are similar to those from ROA. A-VAIC As well as the components of A-VAIC, *i.e.* HCE, INVCE and CEE, are positive and significantly related to ROE in almost all markets in the study which shows that the results are consistent. This consistency in results posits some important allusions. First, the link between HCE and firm performance has been supressed in the original VAIC model because of the superimposition between HCE and SCE. Moreover, this link has been identified in the A-VAIC once the superimposition is eliminated. Second, INVCE (R&D) is a true representative of structural capital unlike in the original VAIC model where it is calculated as the difference between VA and HC. Third, the A-VAIC model produces more consistent results, which implies that the changes to the original VAIC improve the overall efficiency to represent IC resources.

7.3 Policy Implications of the Research

The measurement and benchmarking of IC efficiency have had enormous popularity over the last two decades. This is because different theories such as RB and RD, emphasize the importance of intangible resources for the competitive advantage of a firm. The topic has received further attention since the 1997 Asian financial crisis and 2008 global financial crisis as firms realized that relying solely on physical assets poses significant risks to survival of firms. Therefore, the current study's findings provide several policy implications relevant to policy-makers as well as academicians.

The study's findings exhibit that IC efficiency varies across different regions, *i.e.*, developed, emerging and frontier markets. Our findings show that IC efficiency is better for firms in developed markets than their counterparts in emerging and frontier markets. Continuing the argument by Kolachi and Shah (2013) that IC is necessary for small and big firms and firms in developed as well as developing countries, our findings show that policy makers in emerging and frontier markets can benchmark IC efficiency scores from developed markets. This benchmarking will help firms in emerging and frontier markets increase their IC efficiency to compete in the free-trade agreements era (Burgman & Roos, 2007). These findings might also be useful for potential investors who can determine future IC efficiency of firms before making investment decisions. Investors today are concerned about intangibles' performance along with financial performance. The findings can also be used by rating agencies to evaluate the performance of intangibles and compare IC performance of the firms from different regions.

This study reports a significant, positive relationship between IC efficiency and firm performance, which endorse RB theory. This implies that an increase in IC efficiency leads to better firm performance. Different regulators such as securities and exchange commissions and governments can evaluate IC efficiency as part of firm performance for regulating or listing-delisting of firms. These findings are particularly important for firms' management whereby they can increase investment in intangibles to build a sustainable competitive advantage under the RB theory. Corporate intangibles reporting on annual reports has always been limited because of strict financial reporting standards (Sujan & Abeysekera, 2007; Carvalho *et al.*, 2016). Many authors agree that this issue is pending partly because of underestimation of IC importance (Sakakibara *et al.*, 2010). Mixed results from limited studies have further aggravated the issue. This study's findings provide strong evidence with regard to the importance of IC efficiency that can enable the authorities to alter regulations related to intangibles' reporting.

This study reports a significant, positive relationship between human capital efficiency and firm performance, which endorses RD theory. This implies that an increase in HCE leads to better firm performance. These findings are contrary to those of many studies (Firer & Williams, 2003; Chan, 2009b; Zéghal & Maaloul, 2010; Kamal *et al.*, 2012), which are limited to one country, smaller sample size and/or rely on static estimation. These studies implicitly argue that investment in human resources is considered an expense hence not important for the firms. The findings, however, show that human resources contribute significantly towards value creation and should be considered as an investment as argued by Frederickson *et al.* (2010). These findings are useful for owners (shareholders) who should consider human capital as a strategic resource and hence emphasize its training and development. Furthermore, these findings are particularly important for regulators in service-oriented industries, such as banks, where humans directly determine the quality of products and services being offered. Regulators in these industries should set some minimum standards related to human capital development.

This study also reports a positive, significant relationship between INVCE and firm performance, which endorses OL theory. This implies that an increase in INVCE leads to better firm performance through innovation in products and services. These cross-region findings will be useful for different stakeholders. For example, owners (shareholders) can realize the importance of R&D and increase investment in innovation capital to bring in innovation in products and services to compete in the global market. Since R&D is important for specific industries, such as information technology and pharmaceuticals, regulators of these industries should provide special incentives such as tax incentives on R&D investment to bring in more innovation in products and services as argued by Shah (2006). This is similar to the argument by Hall and Van Reenen (2000) that tax incentives in R&D by the government leads to more R&D accumulation in OECD countries.

This study shows that the relationship between IC and firm performance is dynamic. Tests such as the dynamic OLS and Wooldridge (2002) Test for strict exogeneity show that the relationship between IC and firm performance encounters some econometric problems such as endogeneity. Hence, we use the dynamic panel GMM to overcome this deficiency of not providing efficient, unbiased results. Thus this study enables policy-makers to understand that IC efficiency not only affects firm performance but the opposite is also true. Furthermore, the reverse causal relationship[43] shows that policy-makers should consider IC accumulation as an ongoing process hence the continuation of investment in IC resources is necessary.

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[43] As discussed in chapter 5 that IC leads to better performance in future and past better firm performance also leads to increase in future IC efficiency.

The VAIC model has been well accepted and used by academicians as well as corporates but the model has also been criticized, in general, and its structural capital measure, in particular. We replace structural capital with *Innovation capital* (R&D, as its proxy). We then apply the new A-VAIC to five developed and five emerging markets and note that these adjustments provide theoretically consistent results. Human capital and innovation capital, for example, are positive and statistically significant in almost all markets. Hence, the A-VAIC can be used by the regulators to measure IC efficiency across firms and industries. Since recent studies[44] prohibit the use of the VAIC model in its original form, future researchers can use the A-VAIC model in their research.

Finally, the positive relationship between IC and firm performance during the 2008 global financial crisis indicates that IC efficiency remained unchanged during the crisis. This implies that firms can use IC to increase their value creation when other financial assets become difficult to introduce because of limited funds. This argument is consistent with the findings of Sumedrea (2013) who concludes that IC can be used as a tool for survival during financial turbulence. This finding is also useful for the regulators who can formulate strategies related to the effective use of IC resources during financial crises.

7.4 Research Contributions

This current study contributes to IC literature in several ways. First, the use of a large-scale data set, *i.e.,* three different regions, differentiates this current study from previous studies that rely on small data sets hence it is difficult to generalize the results. Firer and Williams (2003) and Vishnu and Kumar Gupta (2014), for example, attribute their mixed results to the limited scope of their studies, *i.e.,* either a small number of firms or limited years in the sample. Nimtrakoon and Chase (2015) conclude that generalizing the findings of IC studies is difficult for several reasons such as the limited scope of the study. Therefore, the findings of this study based on 15 markets of the world, provide sufficient basis for generalization of the results.

Secondly, this current study finds a significant positive relationship between IC and firm performance, which implies that IC contributes significantly towards value creation. This finding is an important contribution to the IC literature. The finding is useful for policy-makers to justify their investment in IC resources. The significant positive relationship between HCE and firm performance makes it fairly reasonable to justify spending on personnel. Moreover, this finding is useful for policy-makers to formulate effective training and development programmes to enhance the efficiency of human capital. Similarly, the significant positive relationship between innovation capital and firm performance highlights the importance of R&D investment for firm performance.

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[44] See among other Vishnu and Kumar Gupta (2014) and Ståhle *et al.* (2011).

Third, this study finds that the relationship between IC and firm performance is dynamic hence the application of static estimators such as OLS and fixed-effects will produce biased results. This current study, therefore, applies dynamic panel data estimator to measure the true relationship between IC and firm performance in the presence of endogeneity. Such a contribution to the literature can prove a breakthrough since future research can focus on this important econometric aspect of the relationship between IC and firm performance.

Fourth, this current study introduces the A-VAIC model to overcome general criticisms of the original VAIC model. The application of the A-VAIC model to 10 markets provides more consistent results than the original VAIC model. Human capital, for example, is insignificant and/or negatively related to firm performance in the VAIC model but became statistically significant and positive when we applied the A-VAIC. The A-VAIC model can be used by the firms to measure IC efficiency as it truly depicts major components of IC, unlike the VAIC, which contains an ambiguous structural capital component.

7.5 Limitations and Directions for Future Research

7.5.1 Limitations

First, though the dynamic panel GMM estimator solves many econometric problems such as serial correlation and endogeneity, it also has some limitations. For example, as argued by Wintoki *et al.* (2012), GMM uses internally generated instruments (lags of dependent and independent variables) so there is a possibility of weak instruments especially when the number of lags increases. Hence, caution should be exercised if one applies dynamic panel GMM in IC-firm performance studies. Furthermore, this methodology assumes that our model includes all the variables that could possibly influence the dependent and independent variables hence, future unexpected changes in the dependent variable are expectation errors (Hansen & Singleton, 1982). This assumption is very restrictive in empirical research because of the use of proxies and/or omitted variables (Wintoki *et al.*, 2012).

Second, this current study relies on data from publicly listed firms, excluding non-listed and/or private firms because of the unavailability of data. Findings drawn from listed firms can be difficult to generalize to private companies that might have different characteristics such as different patterns of investment in IC resources. Moreover, though our study covers 15 markets across three regions, the findings will be difficult to generalize to other countries because of country-specific factors such as tax exemption on R&D investments, economic development levels and state regulations.

Third, this study used a purely quantitative model to measure IC efficiency hence ignored qualitative factors. Inkinen and Chase (2015) and Díaz-Fernández *et al.* (2015), for example, document that the relationship between IC and firm performance is mediated through different factors such as top management teams' knowledge and the working environment. The introduction of these mediating factors might produce different outcomes related to the IC-firm performance relationship hence the findings of this study should be interpreted carefully.

7.5.2 Directions for Future Research

Future research can be conducted in one of the many directions as follows. In line with the arguments by Inkinen and Chase (2015) that IC works through interactions, future research can focus on the moderating and/or mediating role of corporate governance on the relationship between IC and firm performance. This extension can reveal significant outcomes on how IC efficiency can be increased by improving governance-related factors. Future research can also focus on the role of state regulations in determining the relationship between IC and firm performance.

Future research can also be extended to private firms to see if there are differences in the management of IC resources between listed and private firms. A cross-industry analysis of IC performance can reveal significant outcomes such as industry-specific factors affecting IC efficiency. For example, industries such as pharmaceutical and high-tech, rely more on R&D whereas industries, such as banking and insurance, rely more on human capital to provide better services. These industry-specific factors might produce more insights into the dynamics of IC efficiency.

This study made some important adjustments in the VAIC model and introduces the A-VAIC model. Future research can include other components of IC such as social capital in the A-VAIC model and empirically test if that increases the power of the model to measure IC efficiency. R&D data for frontier markets were not available in our database hence future research can test the A-VAIC model in frontier markets. The application of A-VAIC in frontier markets will test how reliable and consistent A-VAIC is in measuring IC efficiency.

Finally, this study provides a new direction for future research to apply dynamic panel GMM to measure the dynamic nature of the relationship between IC and firm performance. The limitations of GMM discussed in the previous section provide an opportunity for future research to use other instrumental variable regressions, such as 2SLS, provided strictly exogenous external instruments are available.

Appendix A

A.1 Pearson Correlation Matrix between the Dependent and Independent Variables (Developed Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE		ROA	ROE	ATO	P/B	VAIC
Australia	ROA	1							ROA	1				
	ROE	.751**	1						ROE	.751**	1			
	ATO	.386**	.286**	1					ATO	.386**	.286**	1		
	P/B	.471**	.598**	.225**	1				P/B	.471**	.598**	.225**	1	
	HCE	.180**	.173**	-.261**	.118**	1			VAIC	.272**	.270**	-.091**	.219**	1
	SCE	.135**	.146**	-.436**	.123**	.707**	1							
	CEE	.429**	.399**	.789**	.385**	-.295**	-.551**	1						
Austria	ROA	1							ROA	1				
	ROE	.759**	1						ROE	.759**	1			
	ATO	.440**	.333**	1					ATO	.440**	.333**	1		
	P/B	.355**	.434**	.386**	1				P/B	.355**	.434**	.386**	1	
	HCE	.086***	-0.018	-.402**	-0.083***	1			VAIC	.208**	0.066	-.223**	0.03	1
	SCE	0.016	-0.061	-.557**	-.166**	.753**	1							
	CEE	.471**	.398**	.767**	.422**	-.444**	-.698**	1						
Netherlands	ROA	1							ROA	1				
	ROE	.721**	1						ROE	.721**	1			
	ATO	.410**	.202**	1					ATO	.410**	.202**	1		
	P/B	.426**	.511**	.330**	1				P/B	.426**	.511**	.330**	1	
	HCE	.107**	.088*	-.261**	-0.047	1			VAIC	.158**	.109**	-.127**	0.012	1
	SCE	.085*	.155**	-.501**	0	.650**	1							
	CEE	.337**	.198**	.740**	.395**	-.416**	-.704**	1						
Singapore	ROA	1							ROA	1				
	ROE	.709**	1						ROE	.709**	1			
	ATO	.263**	.250**	1					ATO	.263**	.250**	1		
	P/B	.385**	.496**	.145**	1				P/B	.385**	.496**	.145**	1	
	HCE	.267**	.255**	-.238**	0.029***	1			VAIC	.312**	.304**	-.170**	.073**	1
	SCE	.289**	.313**	-.259**	.048**	.769**	1							
	CEE	.418**	.418**	.682**	.351**	-.244**	-.337**	1						

Sweden	ROA	1							ROA	1				
	ROE	.734**	1						ROE	.734**	1			
	ATO	.275**	.139**	1					ATO	.275**	.139**	1		
	P/B	.388**	.487**	.341**	1				P/B	.388**	.487**	.341**	1	
	HCE	.207**	.199**	-.402**	-.072**	1			VAIC	.274**	.277**	-.178**	0.02	1
	SCE	.144**	.173**	-.435**	0.002	.617**	1							
	CEE	.260**	.192**	.775**	.382**	-.426**	-.732**	1						

Note: * Significance at 0.05, ** Significance at 0.01 and **** Significance at 0.10. Control variables were included in every specification but not reported to save space.

A.2 Pearson Correlation Matrix between the Dependent and Independent Variables (Emerging Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE		ROA	ROE	ATO	P/B	VAIC
China	ROA	1							ROA	1				
	ROE	.788**	1						ROE	.788**	1			
	ATO	.265**	.274**	1					ATO	.265**	.274**	1		
	P/B	.305**	.323**	.091**	1				P/B	.305**	.323**	.091**	1	
	HCE	.206**	.255**	-.094**	-.055**	1			VAIC	.222**	.273**	-.077**	-.045**	1
	SCE	.101**	.141**	-.029**	0.006	.712**	1							
	CEE	.622**	.646**	.456**	.261**	.038**	-.159**	1						
Malaysia	ROA	1							ROA	1				
	ROE	.707**	1						ROE	.707**	1			
	ATO	.297**	.216**	1					ATO	.297**	.216**	1		
	P/B	.443**	.519**	.104**	1				P/B	.443**	.519**	.104**	1	
	HCE	.272**	.306**	-.175**	.180**	1			VAIC	.298**	.332**	-.136**	.202**	1
	SCE	.346**	.385**	-.196**	.199**	.749**	1							
	CEE	.460**	.458**	.647**	.368**	-.141**	-.203**	1						
Russia	ROA	1							ROA	1				
	ROE	.700**	1						ROE	.700**	1			
	ATO	.292**	.255**	1					ATO	.292**	.255**	1		
	P/B	.191**	.342**	.204**	1				P/B	.191**	.342**	.204**	1	
	HCE	.240**	.246**	-.151**	.118**	1			VAIC	.315**	.325**	-0.023	.181**	1
	SCE	.213**	.243**	-.111**	.066*	.735**	1							
	CEE	.352**	.366**	.518**	.220**	-.257**	-.500**	1						
South Africa	ROA	1							ROA	1				
	ROE	.785**	1						ROE	.785**	1			
	ATO	.281**	.147**	1					ATO	.281**	.147**	1		
	P/B	.316**	.528**	.130**	1				P/B	.316**	.528**	.130**	1	
	HCE	.179**	.193**	-.271**	.113**	1			VAIC	.227**	.265**	-.163**	.185**	1
	SCE	.173**	.184**	-.328**	.106**	.721**	1							
	CEE	.251**	.333**	.650**	.367**	-.342**	-.517**	1						
Turkey	ROA	1							ROA	1				
	ROE	.796**	1						ROE	.796**	1			
	ATO	.234**	0.044***	1					ATO	.234**	0.044***	1		
	P/B	.195**	.314**	.076**	1				P/B	.195**	.314**	.076**	1	
	HCE	.325**	.255**	-.187**	-0.016	1			VAIC	.344**	.277**	-.155**	0.013	1
	SCE	.217**	.214**	-.136**	0.015	.749**	1							
	CEE	.320**	.359**	.442**	.392**	-.150**	-.256**	1						

Note: * Significance at 0.05, ** Significance at 0.01 and **** Significance at 0.10. Control variables were included in every specification but not reported to save space.

A.3 Pearson Correlation Matrix between the Dependent and Independent Variables (Frontier Markets)

		ROA	ROE	ATO	P/B	HCE	SCE	CEE		ROA	ROE	ATO	P/B	VAIC
Argentina	ROA	1							ROA	1				
	ROE	.717**	1						ROE	.717**	1			
	ATO	.403**	.208**	1					ATO	.403**	.208**	1		
	P/B	.184**	.272**	0.064	1				P/B	.184**	.272**	0.064	1	
	HCE	.119*	0.091***	-.229**	-0.024	1			VAIC	.133**	.189**	-.164**	0.001	1
	SCE	.220**	.116**	-.163**	-0.012	.724**	1							
	CEE	.238**	.416**	.486**	.189**	-.264**	-.430**	1						
Nigeria	ROA	1							ROA	1				
	ROE	-0.052	1						ROE	-0.052	1			
	ATO	-0.021	.549**	1					ATO	-0.021	.549**	1		
	P/B	.494**	-.204**	-.396**	1				P/B	.494**	-.204**	-.396**	1	
	HCE	-.143**	.141**	.102*	-0.069	1			VAIC	.523**	-.458**	-0.09***	.541**	1
	SCE	-0.06	.202**	.161**	-0.056	.873**	1							
	CEE	.451**	-.610**	-.102*	.426**	-.288**	-.256**	1						
Pakistan	ROA	1							ROA	1				
	ROE	.708**	1						ROE	.708**	1			
	ATO	.503**	.303**	1					ATO	.503**	.303**	1		
	P/B	.312**	.427**	.148**	1				P/B	.312**	.427**	.148**	1	
	HCE	.306**	.307**	0.027	.108**	1			VAIC	.347**	.336**	.074*	.160**	1
	SCE	.321**	.343**	-0.014	.090**	.720**	1							
	CEE	.557**	.565**	.623**	.437**	0.025	-0.045	1						
Saudi Arabia	ROA	1							ROA	1				
	ROE	.734**	1						ROE	.734**	1			
	ATO	.565**	.471**	1					ATO	.565**	.471**	1		
	P/B	.401**	.407**	.270**	1				P/B	.401**	.407**	.270**	1	
	HCE	.379**	.274**	-0.039	.187**	1			VAIC	.391**	.286**	-0.023	.200**	1
	SCE	.252**	.140**	-.128**	.105**	.792**	1							
	CEE	.640**	.756**	.635**	.369**	0.064***	-.159**	1						
Ukraine	ROA	1							ROA	1				
	ROE	.720**	1						ROE	.720**	1			
	ATO	.489**	.455**	1					ATO	.489**	.455**	1		
	P/B	-.185**	-0.042	0.024	1				P/B	-.185**	-0.042	0.024	1	
	HCE	.277**	.289**	-.177**	-0.051	1			VAIC	.330**	.375**	-0.042	0.067	1
	SCE	.249**	.303**	-.212**	-.132**	.671**	1							
	CEE	.555**	.543**	.776**	0.074	-.179**	-.313**	1						

Note: * Significance at 0.05, ** Significance at 0.01 and **** Significance at 0.10. Control variables were included in every specification but not reported to save space.

Appendix B

B.1 The Impact of IC on the Firm Performance - OLS Results with ATO as the Dependent Variable

	Model 1			Model 2				
	Intercept	VAIC	Adj-R^2	Intercept	HCE	SCE	CEE	Adj-R^2
				Developed Economies				
Australia	0.064	-0.119*	0.01	0.528*	-0.050*	0.009	0.707*	0.57
	(0.312)	(0.000)		(0.000)	(0.004)	(0.708)	(0.000)	
Austria	0.144	-0.592*	0.03	0.797*	-0.078	0.116	1.055*	0.80
	(0.526)	(0.000)		(0.000)	(0.247)	(0.212)	(0.000)	
Netherlands	0.247***	-0.173*	0.01	0.828*	-0.034	0.220*	0.871*	0.59
	(0.067)	(0.002)		(0.000)	(0.395)	(0.000)	(0.000)	
Singapore	0.147*	-0.246*	0.05	0.908*	-0.111*	0.064***	0.719*	0.47
	(0.008)	(0.000)		(0.000)	(0.000)	(0.093)	(0.000)	
Sweden	0.232**	-0.244*	0.02	0.998*	-0.260*	0.386*	0.798*	0.59
	(0.017)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
				Emerging Economies				
China	-0.359*	-0.112*	0.03	0.724*	-0.174*	0.252*	0.566*	0.26
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Malaysia	-0.252*	-0.176*	0.02	0.909*	-0.089*	-0.026	0.775*	0.42
	(0.000)	(0.000)		(0.000)	(0.000)	(0.490)	(0.000)	
Russia	-0.084	-0.053***	0.02	0.765*	-0.043	0.093**	0.847*	0.44
	(0.396)	(0.080)		(0.000)	(0.139)	(0.012)	(0.000)	
South Africa	0.427*	-0.246*	0.03	0.335*	0.037	-0.265*	0.794*	0.43
	(0.000)	(0.000)		(0.001)	(0.137)	(0.000)	(0.000)	
Turkey	0.051	-0.265*	0.02	1.061*	-0.120**	-0.142	0.788*	0.25
	(0.885)	(0.000)		(0.002)	(0.024)	(0.242)	(0.000)	
				Frontier Economies				
Argentina	-0.409**	-0.197*	0.05	0.245	-0.171**	0.044	0.519*	0.26
	(0.043)	(0.007)		(0.266)	(0.034)	(0.691)	(0.000)	
Nigeria	-0.296**	-0.090*	0.01	0.434***	-0.739*	0.421*	-0.033	0.03
	(0.024)	(0.059)		(0.064)	(0.003)	(0.000)	(0.172)	
Pakistan	-0.658*	0.136*	0.01	1.135*	-0.107**	0.502*	0.967*	0.41
	(0.000)	(0.002)		(0.000)	(0.015)	(0.000)	(0.000)	
Saudi Arabia	-1.012*	-0.030	0.01	0.588*	-0.057	-0.178	0.973*	0.42
	(0.000)	(0.488)		(0.006)	(0.251)	(0.399)	(0.000)	
Ukraine	-0.038	-0.081	0.01	1.036*	-0.278*	0.263*	0.739*	0.49
	(0.745)	(0.111)		(0.000)	(0.000)	(0.000)	(0.000)	

Note: This table presents standard coefficients (p-values in parentheses) of OLS results with ATO as dependent variable; * ** and *** show significance at 0.01, 0.05 and 0.1 level, respectively. Control variables and year dummies were included in every specification.

Source: Author's calculations

B.2 The Impact of IC on the Firm Performance - OLS Results with P/B as the Dependent Variable)

	Model 1			Model 2				
	Intercept	VAIC	Adj-R^2	Intercept	HCE	SCE	CEE	Adj-R^2
				Developed Economies				
Australia	0.528*	0.253*	0.11	1.954*	-0.086*	0.699*	0.519*	0.35
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Austria	0.502*	0.041	0.04	1.525*	-0.120	0.504*	0.348*	0.25
	(0.000)	(0.529)		(0.000)	(0.100)	(0.000)	(0.000)	
Netherlands	0.950*	-0.011	0.10	2.049*	-0.179*	0.665*	0.450*	0.38
	(0.000)	(0.758)		(0.000)	(0.000)	(0.000)	(0.000)	
Singapore	0.114**	0.067*	0.06	1.084*	-0.033	0.407*	0.411*	0.20
	(0.025)	(0.000)		(0.000)	(0.136)	(0.000)	(0.000)	
Sweden	0.951*	0.016	0.08	2.201*	-0.198*	0.703*	0.525*	0.40
	(0.000)	(0.556)		(0.000)	(0.000)	(0.000)	(0.000)	
				Emerging Economies				
China	0.320*	-0.068*	0.11	0.846*	-0.074*	0.039	0.315*	0.19
	(0.000)	(0.000)		(0.000)	(0.000)	(0.339)	(0.000)	
Malaysia	-0.431*	0.231*	0.06	0.849*	0.073*	0.496*	0.460*	0.24
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Russia	0.154	0.353*	0.15	1.080*	0.126***	0.360*	0.391*	0.20
	(0.477)	(0.000)		(0.000)	(0.050)	(0.001)	(0.000)	
South Africa	0.457*	0.222*	0.08	1.924*	-0.085*	0.957*	0.572*	0.37
	(0.000)	(0.000)		(0.000)	(0.009)	(0.000)	(0.000)	
Turkey	0.585*	0.005	0.05	1.679*	-0.074**	0.353*	0.488*	0.28
	(0.006)	(0.847)		(0.000)	(0.016)	(0.000)	(0.000)	
				Frontier Economies				
Argentina	0.020	0.025	0.03	0.272	0.014	0.030	0.147*	0.04
	(0.869)	(0.658)		(0.162)	(0.836)	(0.785)	(0.002)	
Nigeria	-2.284*	0.810*	0.31	-1.315*	0.330	-0.028	0.324*	0.20
	(0.000)	(0.000)		(0.000)	(0.360)	(0.840)	(0.000)	
Pakistan	0.284**	0.181*	0.14	1.116*	0.165*	-0.318*	0.673*	0.34
	(0.021)	(0.000)		(0.000)	(0.001)	(0.022)	(0.000)	
Saudi Arabia	1.918*	0.108*	0.42	2.865*	0.001	0.387*	0.347*	0.59
	(0.000)	(0.000)		(0.000)	(0.962)	(0.000)	(0.000)	
Ukraine	-0.030	0.345*	0.16	-0.297	0.360**	-0.616**	0.094	0.16
	(0.897)	(0.005)		(0.439)	(0.042)	(0.018)	(0.154)	

Note: This table presents standard coefficients (p-values in parentheses) of OLS results with P/B as dependent variable; * ** and *** show significance at 0.01, 0.05 and 0.1 level, respectively. Control variables and year dummies were included in every specification.

Source: Author's calculations

Appendix C

C.1 The Impact of IC on Firm Performance - Fixed Effect Results with ROE as the Dependent Variable)

	Model 1			Model 2				
	Intercept	VAIC	R^2	Intercept	HCE	SCE	CEE	R^2
				Developed Economies				
Australia	1.953*	0.761*	0.09	4.198*	0.109*	0.861*	0.764*	0.38
	(0.000)	(0.000)		(0.000)	(0.005)	(0.000)	(0.000)	
Austria	2.269*	0.290*	0.05	4.926*	-0.157***	1.405*	0.806*	0.30
	(0.000)	(0.002)		(0.000)	(0.096)	(0.000)	(0.000)	
Netherlands	2.892*	0.036	0.09	4.760*	-0.234*	1.275*	0.545*	0.30
	(0.000)	(0.579)		(0.000)	(0.000)	(0.000)	(0.000)	
Singapore	1.828*	0.680*	0.12	4.464*	0.036	1.144*	0.827*	0.41
	(0.000)	(0.000)		(0.000)	(0.255)	(0.000)	(0.000)	
Sweden	2.385*	0.503*	0.10	5.051*	-0.116**	1.392*	0.885*	0.39
	(0.000)	(0.000)		(0.000)	(0.048)	(0.000)	(0.000)	
				Emerging Economies				
China	1.306*	0.583*	0.14	4.019*	0.132*	0.806*	0.958*	0.50
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Malaysia	1.369*	0.552*	0.11	4.289*	0.052**	1.202*	0.967*	0.44
	(0.000)	(0.000)		(0.000)	(0.031)	(0.000)	(0.000)	
Russia	1.175*	1.059*	0.12	4.295*	0.033	1.436*	0.900*	0.40
	(0.000)	(0.000)		(0.000)	(0.601)	(0.000)	(0.000)	
South Africa	2.720*	0.328*	0.13	4.469*	-0.030	1.097*	0.688*	0.38
	(0.000)	(0.000)		(0.000)	(0.461)	(0.000)	(0.000)	
Turkey	2.086*	0.299*	0.01	3.396*	0.089***	0.399*	0.457*	0.21
	(0.000)	(0.000)		(0.000)	(0.097)	(0.002)	(0.000)	
				Frontier Economies				
Argentina	1.383*	0.575*	0.08	3.199*	0.105	0.754	0.583*	0.30
	(0.000)	(0.000)		(0.000)	(0.838)	(0.000)	(0.000)	
Nigeria	2.986*	-0.791*	0.20	2.045*	-0.633***	0.318***	0.589*	0.29
	(0.000)	(0.000)		(0.000)	(0.080)	(0.084)	(0.000)	
Pakistan	1.760*	0.688*	0.12	4.392*	0.090***	1.042*	0.967*	0.47
	(0.000)	(0.000)		(0.000)	(0.097)	(0.000)	(0.000)	
Saudi Arabia	0.888*	0.892*	0.09	4.559*	0.064	1.772*	0.891*	0.60
	(0.000)	(0.000)		(0.000)	(0.360)	(0.000)	(0.000)	
Ukraine	0.772*	0.960*	0.15	4.153*	-0.021	1.459*	0.967*	0.45
	(0.000)	(0.000)		(0.000)	(0.823)	(0.000)	(0.000)	

This table presents results from fixed-effects estimation with ROE as dependant variable. *, ** and *** represent significance at 0.01, 0.05 and 0.10 respectively. Control variables and year dummies were included in every specification.

Source: Author's calculations

C.2 The Impact of IC on the Firm Performance - Fixed Effect Results with ATO as the Dependent Variable)

	Model 1			Model 2				
	Intercept	VAIC	R^2	Intercept	HCE	SCE	CEE	R^2
				Developed Economies				
Australia	-0.363*	0.221*	0.00	0.342*	0.017	0.096*	0.437*	0.56
	(0.000)	(0.000)		(0.000)	(0.230)	(0.000)	(0.000)	
Austria	-0.600*	0.021	0.00	-0.236*	0.001	-0.050	0.365*	0.80
	(0.000)	(0.445)		(0.004)	(0.982)	(0.439)	(0.000)	
Netherlands	-0.038	0.054**	0.00	0.296*	0.069*	0.072***	0.390*	0.57
	(0.353)	(0.012)		(0.000)	(0.001)	(0.080)	(0.000)	
Singapore	-0.291*	0.085*	0.00	0.486*	-0.027**	-0.034	0.521*	0.47
	(0.000)	(0.000)		(0.000)	(0.040)	(0.146)	(0.000)	
Sweden	-0.198*	0.222*	0.03	0.288*	0.122*	0.126*	0.344*	0.43
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
				Emerging Economies				
China	-0.699*	0.179*	0.00	0.475*	-0.004	0.244*	0.459*	0.22
	(0.000)	(0.000)		(0.000)	(0.421)	(0.000)	(0.000)	
Malaysia	-0.619*	0.098*	0.01	0.388*	-0.011	0.102*	0.486*	0.41
	(0.000)	(0.000)		(0.000)	(0.244)	(0.000)	(0.000)	
Russia	-0.093*	0.100*	0.01	0.303*	-0.019	-0.005	0.383*	0.44
	(0.002)	(0.000)		(0.000)	(0.177)	(0.734)	(0.000)	
South Africa	0.153*	0.006*	0.01	0.354*	0.047*	-0.026	0.436*	0.42
	(0.000)	(0.702)		(0.000)	(0.004)	(0.413)	(0.000)	
Turkey	-0.295**	0.116*	0.01	0.420*	0.031	0.075	0.323*	0.19
	(0.012)	(0.000)		(0.002)	(0.243)	(0.239)	(0.000)	
				Frontier Economies				
Argentina	-0.853*	0.177*	0.01	0.163***	0.070***	-0.051	0.441*	0.26
	(0.000)	(0.000)		(0.076)	(0.066)	(0.389)	(0.000)	
Nigeria	-0.685*	0.120***	0.00	-0.762**	0.318	-0.082	0.059***	0.00
	(0.000)	(0.050)		(0.013)	(0.279)	(0.581)	(0.061)	
Pakistan	-0.451*	0.098*	0.01	0.417*	-0.079*	0.106*	0.450*	0.40
	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)	(0.000)	
Saudi Arabia	-1.759*	0.367*	0.00	0.129	-0.005	0.081	0.670*	0.42
	(0.000)	(0.000)		(0.196)	(0.839)	(0.371)	(0.000)	
Ukraine	-0.334*	0.082**	0.01	0.361*	-0.147*	0.111**	0.391*	0.49
	(0.000)	(0.021)		(0.000)	(0.000)	(0.044)	(0.000)	

This table presents results from fixed-effects estimation with ATO as dependent variable; *, ** and *** represent significance at 0.01, 0.05 and 0.10, respectively. Control variables and year dummies were included in every specification.

Source: Author's calculations

C.3 The Impact of IC on Firm Performance - Fixed Effects Results with P/B as the Dependent Variable

	Model 1			Model 2				
	Intercept	VAIC	R^2	Intercept	HCE	SCE	CEE	R^2
				Developed Economies				
Australia	0.474*	0.326*	0.11	1.653*	-0.045	0.475*	0.385*	0.34
	(0.000)	(0.000)		(0.000)	(0.104)	(0.000)	(0.000)	
Austria	0.449*	0.076	0.06	1.366*	-0.095	0.582*	0.190**	0.05
	(0.000)	(0.155)		(0.000)	(0.108)	(0.000)	(0.019)	
Netherlands	0.971*	-0.003	0.11	1.594*	-0.068**	0.403*	0.255*	0.35
	(0.000)	(0.916)		(0.000)	(0.025)	(0.000)	(0.000)	
Singapore	0.006	0.184*	0.05	0.643*	0.059*	0.137*	0.260*	0.18
	(0.854)	(0.000)		(0.000)	(0.004)	(0.000)	(0.000)	
Sweden	0.771*	0.237*	0.06	1.691*	-0.050	0.370*	0.369*	0.37
	(0.000)	(0.000)		(0.000)	(0.193)	(0.000)	(0.000)	
				Emerging Economies				
China	0.683*	0.093*	0.08	1.461*	-0.007	-0.039	0.333*	0.18
	(0.000)	(0.000)		(0.000)	(0.523)	(0.304)	(0.000)	
Malaysia	-0.240*	0.128*	0.06	0.519*	0.007	0.257*	0.273*	0.23
	(0.000)	(0.000)		(0.000)	(0.591)	(0.000)	(0.000)	
Russia	0.793*	0.011	0.12	1.064*	-0.042	0.018	0.255*	0.16
	(0.000)	(0.796)		(0.000)	(0.405)	(0.868)	(0.000)	
South Africa	0.618*	0.102*	0.08	1.305*	-0.030	0.422*	0.317*	0.34
	(0.000)	(0.000)		(0.000)	(0.294)	(0.000)	(0.000)	
Turkey	0.537*	0.019	0.06	1.120*	0.057***	0.130***	0.247*	0.26
	(0.000)	(0.444)		(0.000)	(0.056)	(0.073)	(0.000)	
				Frontier Economies				
Argentina	0.003	0.090	0.05	0.510**	-0.017	0.006	0.262*	0.07
	(0.984)	(0.226)		(0.028)	(0.846)	(0.964)	(0.000)	
Nigeria	-1.023*	0.150**	0.20	-1.431*	0.265	-0.419**	0.009	0.05
	(0.000)	(0.028)		(0.000)	(0.425)	(0.013)	(0.780)	
Pakistan	0.218*	0.171*	0.14	1.057*	-0.015	0.250**	0.355*	0.27
	(0.000)	(0.000)		(0.000)	(0.704)	(0.015)	(0.000)	
Saudi Arabia	1.826*	0.186*	0.41	2.382*	0.082***	-0.019	0.195*	0.56
	(0.000)	(0.000)		(0.000)	(0.066)	(0.890)	(0.000)	
Ukraine	0.488**	0.081	0.15	1.895*	-0.550**	-0.017	0.737*	0.09
	(0.028)	(0.590)		(0.000)	(0.013)	(0.956)	(0.000)	

This table presents results from fixed-effects estimation with P/B ratio as dependent variable; *, ** and *** represent significance at 0.01, 0.05 and 0.10, respectively. Control variables and year dummies were included in every specification.

Source: Author’s calculations

Appendix D

D.1 The Woolridge Test for Autocorrelation

	ROA	ROE	ATO	P/B
		Developed Markets		
Australia	21.77*	21.45*	24.44*	206.34*
	(0.000)	(0.000)	(0.000)	(0.000)
Austria	1.20	0.91	0.64	78.72*
	(0.278)	(0.343)	(0.426)	(0.000)
Netherlands	9.84*	7.80*	29.82*	41.18*
	(0.002)	(0.006)	(0.000)	(0.000)
Singapore	45.42*	46.20*	137.10*	87.58*
	(0.000)	(0.000)	(0.000)	(0.000)
Sweden	10.82*	9.32*	71.56*	108.79*
	(0.001)	(0.003)	(0.000)	(0.000)
		Emerging Markets		
China	149.18*	131.21*	749.85*	1009.68*
	(0.000)	(0.000)	(0.000)	(0.000)
Malaysia	24.98*	18.26*	94.65*	196.69*
	(0.000)	(0.000)	(0.000)	(0.000)
Russia	28.15*	24.62*	80.16*	67.54*
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	25.24*	35.07*	87.12*	197.78*
	(0.000)	(0.000)	(0.000)	(0.000)
Turkey	5.88**	4.41**	2.32	16.97*
	(0.016)	(0.037)	(0.128)	(0.000)
		Frontier Markets		
Argentina	10.70*	10.96*	7.19*	54.79*
	(0.002)	(0.001)	(0.009)	(0.000)
Nigeria	34.54*	39.33*	51.53*	127.68*
	(0.000)	(0.000)	(0.000)	(0.000)
Pakistan	34.35*	25.65*	83.87*	120.51*
	(0.000)	(0.000)	(0.000)	(0.000)
Saudi Arabia	12.81*	13.54*	17.86*	68.32*
	(0.000)	(0.000)	(0.000)	(0.000)
Ukraine	19.72*	18.89*	51.71*	2.61
	(0.000)	(0.000)	(0.000)	(0.112)

Note: This table presents results of Woolridge test for autocorrelation; *p*-values are in parentheses; * and ** show significance at 0.01 and 0.05, respectively.

Source: Author’s calculations

Appendix E

E.1 The Dynamic Panel Data Estimation: Two Step Robust System GMM Results with ATO as the Dependent Variable

	Model 1		Model 2			
	L.ATO	VAIC	L.ATO	HCE	SCE	CEE
			Developed Economies			
Australia	0.782*	-0.062	0.618*	-0.048	0.053	0.310*
	(0.000)	(0.169)	(0.000)	(0.138)	(0.183)	(0.000)
Austria	1.017*	0.045	0.925*	-0.003	0.062	0.124
	(0.000)	(0.424)	(0.000)	(0.943)	(0.144)	(0.531)
Netherlands	0.946*	0.031	0.851*	0.036	0.035	0.198***
	(0.000)	(0.392)	(0.000)	(0.292)	(0.499)	(0.071)
Singapore	0.831*	0.026	0.802*	-0.009	0.075**	0.207*
	(0.000)	(0.274)	(0.000)	(0.622)	(0.035)	(0.000)
Sweden	1.021*	0.027	0.957*	0.045	0.004	0.095***
	(0.000)	(0.409)	(0.000)	(0.299)	(0.903)	(0.064)
			Emerging Economies			
China	0.942*	0.044	0.720*	-0.329*	0.663**	0.285*
	(0.000)	(0.465)	(0.000)	(0.008)	(0.023)	(0.000)
Malaysia	0.750*	-0.044	0.636*	-0.022	0.036	0.316*
	(0.000)	(0.294)	(0.000)	(0.732)	(0.727)	(0.000)
Russia	0.894*	-0.006	0.874*	-0.030	0.047	0.127
	(0.000)	(0.827)	(0.000)	(0.773)	(0.585)	(0.255)
South Africa	0.994*	0.007	0.931*	0.042	-0.033	0.122*
	(0.000)	(0.812)	(0.000)	(0.144)	(0.286)	(0.001)
Turkey	0.879*	0.009	0.860*	0.031	-0.041	0.170*
	(0.000)	(0.743)	(0.000)	(0.469)	(0.494)	(0.001)
			Frontier Economies			
Argentina	0.947*	-0.046	0.862*	-0.171**	0.178**	0.095**
	(0.000)	(0.485)	(0.000)	(0.039)	(0.031)	(0.047)
Nigeria	0.967*	0.063	0.907*	-0.055	0.137	0.063
	(0.000)	(0.301)	(0.000)	(0.814)	(0.221)	(0.363)
Pakistan	0.956*	0.093*	0.907*	0.058	-0.045	0.126*
	(0.000)	(0.000)	(0.000)	(0.200)	(0.452)	(0.000)
Saudi Arabia	0.903*	0.012	0.899*	0.015	0.033	0.170*
	(0.000)	(0.487)	(0.000)	(0.550)	(0.729)	(0.006)
Ukraine	0.747*	-0.09	0.644*	-0.150	0.123	0.311*
	(0.000)	(0.860)	(0.000)	(0.142)	(0.104)	(0.000)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10 level, respectively. Control variables and time dummies are included in all specifications.

Source: Author's calculations

E.2 The Dynamic Panel Data Estimation: Two Step Robust System GMM Results with P/B as the Dependent Variable

	Model 1		Model 2			
	L.P/B	VAIC	L.P/B	HCE	SCE	CEE
			Developed Economies			
Australia	0.656*	0.083	0.723*	-0.094	0.278*	0.203*
	(0.000)	(0.321)	(0.000)	(0.402)	(0.003)	(0.000)
Austria	0.749*	0.111**	0.702	-0.391	0.719	0.194
	(0.000)	(0.035)	(0.797)	(0.912)	(0.638)	(0.585)
Netherlands	0.782*	0.032	0.772*	-0.076*	0.249*	0.144*
	(0.000)	(0.609)	(0.000)	(0.000)	(0.000)	(0.004)
Singapore	0.784*	-0.008	0.678*	0.082	-0.022	0.145*
	(0.000)	(0.874)	(0.000)	(0.089)	(0.779)	(0.000)
Sweden	0.415**	0.133***	0.667*	-0.100**	0.414**	0.309*
	(0.010)	(0.063)	(0.000)	(0.022)	(0.016)	(0.000)
			Emerging Economies			
China	0.791*	-0.034**	1.083*	-0.029	0.073	0.030
	(0.000)	(0.011)	(0.000)	(0.722)	(0.634)	(0.291)
Malaysia	0.798*	0.080	0.673*	0.023	0.194	0.185*
	(0.000)	(0.195)	(0.000)	(0.814)	(0.175)	(0.000)
Russia	0.471*	0.015	0.581*	-0.021	0.161	0.116***
	(0.002)	(0.934)	(0.000)	(0.866)	(0.384)	(0.086)
South Africa	0.878*	0.032	0.742*	-0.042	0.299*	0.185*
	(0.000)	(0.257)	(0.000)	(0.350)	(0.002)	(0.000)
Turkey	0.848*	0.040	0.887*	0.001	0.017	0.133*
	(0.000)	(0.183)	(0.000)	(0.980)	(0.853)	(0.001)
			Frontier Economies			
Argentina	0.544*	0.064	0.599*	-0.161	0.263***	0.099***
	(0.000)	(0.528)	(0.000)	(0.178)	(0.058)	(0.079)
Nigeria	0.959*	0.109	0.883*	0.040	-0.017	-0.015
	(0.000)	(0.322)	(0.000)	(0.856)	(0.858)	(0.865)
Pakistan	0.838*	0.087**	0.926*	0.018	0.033	0.144*
	(0.000)	(0.033)	(0.000)	(0.700)	(0.839)	(0.000)
Saudi Arabia	0.738*	0.033	0.643*	-0.038	0.316**	0.141*
	(0.000)	(0.106)	(0.000)	(0.311)	(0.037)	(0.000)
Ukraine	0.641*	0.347**	0.752*	0.689	-0.811	0.060
	(0.000)	(0.021)	(0.000)	(0.139)	(0.137)	(0.442)

Note: * ** and *** represent significance at 0.01, 0.05 and 0.10 level, respectively. Control variables and time dummies are included in all specifications.

Source: Author’s calculations

Appendix F

F.1 The Dynamic Panel Data Estimation: Diagnostic Tests with ATO as the Dependent Variable

	Model 1 (VAIC)						Model 2 (HCE,SCE,CEE)					
	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.
					Developed Economies							
Australia	0.000	0.808	0.116	0.758	34	2557	0.000	0.407	0.140	0.100	96	2557
Austria	0.031	0.508	0.397	0.191	34	378	0.042	0.462	0.488	0.604	68	378
Netherlands	0.016	0.157	0.529	0.841	34	468	0.021	0.119	0.334	0.168	68	468
Singapore	0.000	0.640	0.227	0.554	34	3056	0.000	0.694	0.107	0.992	84	3056
Sweden	0.000	0.307	0.215	0.257	48	1232	0.000	0.409	0.248	0.303	68	1232
					Emerging Economies							
China	0.000	0.000	0.310	0.064	22	9597	0.743	0.279	0.996	0.056	52	9597
Malaysia	0.000	0.089	0.062	0.302	42	4009	0.000	0.353	0.101	0.785	68	4009
Russia	0.000	0.467	0.300	0.100	42	2723	0.040	0.857	0.100	0.599	52	2723
South Africa	0.000	0.051	0.832	0.906	34	1165	0.000	0.053	0.588	0.816	96	1165
Turkey	0.018	0.232	0.514	0.781	34	1013	0.036	0.227	0.201	0.132	68	1013
					Frontier Economies							
Argentina	0.015	0.316	0.426	0.144	34	348	0.019	0.162	0.523	0.663	68	348
Nigeria	0.100	0.083	0.260	0.955	48	324	0.112	0.101	0.397	0.276	72	324
Pakistan	0.000	0.559	0.019	0.709	42	918	0.000	0.707	0.182	0.140	68	918
Saudi Arabia	0.028	0.076	0.074	0.876	30	636	0.007	0.076	0.134	0.338	96	636
Ukraine	0.001	0.679	0.150	0.628	30	895	0.002	0.972	0.153	0.293	68	895

Note: AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively; Han.J,O.Id is Hansen J. Test for over identification of instruments; the Han.J.Diff is the Difference-in-Hansen Test for exogeneity of instruments; No. INS is the number of instruments used in each specification and Obs is the number of observations.

Source: Author’s calculations

F.2 The Dynamic Panel Data Estimation: Diagnostic Tests with P/B as the Dependent Variable

	Model 1 (VAIC)						Model 2 (HCE,SCE,CEE)					
	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.	AR1	AR2	Han.J. O.Id	Han.J. Diff	No. INS	Obs.
Developed Economies												
Australia	0.000	0.484	0.244	0.573	42	2422	0.000	0.290	0.395	0.839	84	2422
Austria	0.007	0.100	0.396	0.462	42	358	0.800	0.978	0.432	0.464	52	358
Netherlands	0.004	0.052	0.227	0.368	42	460	0.001	0.058	0.755	0.991	84	460
Singapore	0.000	0.219	0.075	0.520	30	2677	0.000	0.837	0.800	0.845	84	2677
Sweden	0.031	0.076	0.119	0.764	42	1170	0.248	0.354	0.349	0.372	52	1170
Emerging Economies												
China	0.000	0.275	0.547	0.579	30	7557	0.100	0.749	0.998	0.466	52	7557
Malaysia	0.000	0.410	0.100	0.001	60	3918	0.000	0.555	0.003	0.237	84	3918
Russia	0.003	0.175	0.021	0.656	34	672	0.000	0.149	0.188	0.313	96	672
South Africa	0.000	0.254	0.112	0.394	34	1126	0.000	0.175	0.095	0.619	68	1126
Turkey	0.000	0.587	0.180	0.930	42	963	0.000	0.251	0.011	0.950	68	963
Frontier Economies												
Argentina	0.026	0.047	0.814	0.560	60	286	0.008	0.240	0.750	0.627	68	286
Nigeria	0.131	0.638	0.762	0.846	34	325	0.100	0.600	0.551	0.790	68	325
Pakistan	0.000	0.400	0.253	0.332	42	898	0.000	0.342	0.056	0.304	68	898
Saudi Arabia	0.000	0.143	0.215	0.182	60	569	0.000	0.285	0.262	0.622	68	569
Ukraine	0.003	0.457	0.997	0.594	60	230	0.005	0.356	0.996	0.992	68	230

Note: AR1 and AR2 are tests for first and second order serial correlation in the first-difference residuals, respectively; Han.J,O.Id is the Hansen J. Test for over identification of instruments; Han.J.Diff is the Difference-in-Hansen Test for exogeneity of instruments; No. INS is the number of instruments used in each specification and Obs is the number of observations.

Source: Author’s calculations

References

Abeysekera, I. (2010). The influence of board size on intellectual capital disclosure by Kenyan listed firms. *Journal of Intellectual Capital, 11*(4), 504-518.

Aguiar, L. (2009). *Applying knowledge management for research and development in the pharmaceutical industry*: ProQuest.

Ahangar, R. G. (2011). The relationship between intellectual capital and financial performance: An empirical investigation in an Iranian company. *African Journal of Business Management, 5*(1), 88.

Alipour, M. (2012). The effect of intellectual capital on firm performance: an investigation of Iran insurance companies. *Measuring business excellence, 16*(1), 53-66.

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic management journal, 14*(1), 33-46.

Andriessen, D. (2004). IC valuation and measurement: classifying the state of the art. *Journal of Intellectual Capital, 5*(2), 230-242.

Appuhami, B. R. (2007). The impact of intellectual capital on investors' capital gains on shares: an empirical investigation of Thai banking, finance and insurance sector. *International Management Review, 3*(2), 14-25.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies, 58*(2), 277-297.

Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational behavior and human decision processes, 82*(1), 150-169.

Baltagi, B. (2008). *Econometric analysis of panel data* (Vol. 1): John Wiley & Sons.

Baltas, N. K., Baltas, N. C., & Karras, K. N. (2003). *Investment in the Processing of Agricultural Products and Food in Greece*: Nova Publishers.

Bandt, J. D. (1999). The concept of labour and competence requirements in a service economy. *Service Industries Journal, 19*(1), 1-17.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management, 17*(1), 99-120.

Bassi, L. J. (1997). Harnessing the power of intellectual capital. *Training and Development, 51*, 25-30.

Baum, C. F. (2006). *An introduction to modern econometrics using Stata*: Stata press.

Becker, B. (2013). *The Determinants of R&D Investment: A Survey of the Empirical Research*. Retrieved from

Berzkalne, I., & Zelgalve, E. (2014). Intellectual Capital and Company Value. *Procedia-Social and Behavioral Sciences, 110*, 887-896.

Bharathi Kamath, G. (2008). Intellectual capital and corporate performance in Indian pharmaceutical industry. *Journal of Intellectual Capital, 9*(4), 684-704.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics, 87*(1), 115-143.

Boekestein, B. (2009). Acquisitions reveal the hidden intellectual capital of pharmaceutical companies. *Journal of Intellectual Capital, 10*(3), 389-400.

Bollen, L., Vergauwen, P., & Schnieders, S. (2005). Linking intellectual capital and intellectual property to company performance. *Management Decision, 43*(9), 1161-1185.

Bontis, N. (1999). Managing organisational knowledge by diagnosing intellectual capital: framing and advancing the state of the field. *International Journal of technology management, 18*(5), 433-462.

Bontis, N. (2001). Assessing knowledge assets: a review of the models used to measure intellectual capital. *International journal of management reviews, 3*(1), 41-60.

Bontis, N. (2004). National intellectual capital index: a United Nations initiative for the Arab region. *Journal of Intellectual Capital, 5*(1), 13-39.

Bontis, N., Bart, C. K., Nazari, J. A., & Herremans, I. M. (2007). Extended VAIC model: measuring intellectual capital components. *Journal of Intellectual Capital, 8*(4), 595-609.

Booth, R. (1998). The measurement of intellectual capital. *Management Accounting Research, 76*, 26-28.
Boulton, R. E., Libert, B. D., & Samek, S. M. (2000). A business model for the new economy. *Journal of Business Strategy, 21*(4), 29-35.
Brătianu, C., & Orzea, I. (2009). Emergence of the cognitive-emotional knowledge dyad. *Review of International Comparative Management, 10*(5), 893-902.
Brennan, N., & Connell, B. (2000). Intellectual capital: current issues and policy implications. *Journal of Intellectual Capital, 1*(3), 206-240.
Brooking. (1996). Intellectual capital: Core asset for the third millennium enterprise. *International Thomson Business Press*.
Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance, 64*(1), 151-185.
Bueno, E., Salmador, M. P., & Rodríguez, Ó. (2004). The role of social capital in today's economy: empirical evidence and proposal of a new model of intellectual capital. *Journal of Intellectual Capital, 5*(4), 556-574.
Burgman, & Roos, G. (2007). The importance of intellectual capital reporting: evidence and implications. *Journal of Intellectual Capital, 8*(1), 7-51. doi:http://dx.doi.org/10.1108/14691930710715051
Burgman, Roos, G., Ballow, J., & Thomas, R. (2005). No longer "out of sight, out of mind": Intellectual capital approach in AssetEconomics Inc. and Accenture LLP. *Journal of Intellectual Capital, 6*(4), 588-614.
Cabrita, R. M., & Vaz, J. (2005). Intellectual capital and value creation: evidence from the Portuguese banking industry. *The Electronic Journal of Knowledge Management, 4*(1), 11-20.
Cahill, D., & Myers, P. (2000). *Intellectual capital and accounting concepts: unresolved issues in human resource accounting.* Paper presented at the Annual Conference of the British Accounting Association, Manchester.
Cañibano, L., Garcia-Ayuso, M., & Sánchez, P. (2000). Accounting for intangibles: a literature review. *Journal of Accounting Literature, 19*, 102-130.
Carvalho, C., Rodrigues, A. M., & Ferreira, C. (2016). The Recognition of Goodwill and Other Intangible Assets in Business Combinations–The Portuguese Case. *Australian Accounting Review, 26*(1), 4-20.
Čater, T., & Čater, B. (2009). (In) tangible resources as antecedents of a company's competitive advantage and performance. *Journal for East European Management Studies*, 186-209.
Chan, K. H. (2009a). Impact of intellectual capital on organisational performance: an empirical study of companies in the Hang Seng Index (part 1). *Learning Organization, The, 16*(1), 4-21.
Chan, K. H. (2009b). Impact of intellectual capital on organisational performance: an empirical study of companies in the Hang Seng Index (Part 2). *Learning Organization, The, 16*(1), 22-39.
Charbaji, A. (2011). *Applied Econometrics Using Eviews, SPSS And Excel With Applications In Arab Countries*: AuthorHouse Publishing.
Chauvin, K. W., & Hirschey, M. (1993). Advertising, R&D expenditures and the market value of the firm. *Financial management*, 128-140.
Chen, Cheng, & Hwang. (2005). An empirical investigation of the relationship between intellectual capital and firms' market value and financial performance. *Journal of Intellectual Capital, 6*(2), 159-176.
Chen, T. (2013). Do investors herd in global stock markets? *Journal of Behavioral Finance, 14*(3), 230-239.
Cheng, M.-Y., Lin, J.-Y., Hsiao, T.-Y., & Lin, T. W. (2008). Censoring model for evaluating intellectual capital value drivers. *Journal of Intellectual Capital, 9*(4), 639-654.
Choi, I. (2001). Unit root tests for panel data. *Journal of international money and Finance, 20*(2), 249-272.
Choong, K. K. (2008). Intellectual capital: definitions, categorization and reporting models. *Journal of Intellectual Capital, 9*(4), 609-638.
Clarke, M., Seng, D., & Whiting, R. H. (2011). Intellectual capital and firm performance in Australia. *Journal of Intellectual Capital, 12*(4), 505-530.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative science quarterly*, 128-152.
Colley, J. R., & Volkan, A. G. (1988). Accounting for goodwill. *Accounting Horizons, 2*(1), 35-41.
Curado, C. (2008). Perceptions of knowledge management and intellectual capital in the banking industry. *Journal of Knowledge Management, 12*(3), 141-155.
Dahlman, C. K., Auguste Tano; Vishwanath, Tara. (1998). *World development report 1998/1999 : knowledge for development*. Retrieved from Washington, DC: http://documents.worldbank.org/curated/en/1998/09/17396270/world-development-report-199899-knowledge-development
Davis, S., & Davidson, B. (1992). *2020 Vision*: Simon and Schuster.
De Jong, A., Kabir, R., & Nguyen, T. T. (2008). Capital structure around the world: The roles of firm- and country-specific determinants. *Journal of Banking & Finance, 32*(9), 1954-1969.
Deeds, D. L., & Decarolis, D. M. (1999). The impact of stocks and flows of organizational knowledge on firm performance: An empirical investigation of the biotechnology industry. *Strategic management journal*.
Demediuk, P. (2002). Intellectual capital reporting: New accounting for the new economy. *Asian academy of management journal, 7*(1), 57-74.
Derby, M. (2012). Knowledge-based industries - New knowledge industries. *Te Ara - the Encyclopedia of New Zealand.* Retrieved from http://www.TeAra.govt.nz/en/knowledge-based-industries/page-1
Díaz-Fernández, M. C., González-Rodríguez, M. R., & Simonetti, B. (2015). Top management team's intellectual capital and firm performance. *European Management Journal*.
Diefenbach, T. (2006). Intangible resources: a categorial system of knowledge and other intangible assets. *Journal of Intellectual Capital, 7*(3), 406-420.
Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *Stata journal, 3*(2), 168-177.
Dyer, J. H., & Singh, H. (1998). The relational view: cooperative strategy and sources of interorganizational competitive advantage. *Academy of management Review, 23*(4), 660-679.
Dzinkowski, R. (2000). The value of intellectual capital. *Journal of Business Strategy, 21*(4), 3-3.
Ederer, P. (2006). *Innovation at Work: The European Human Capital Index*: Lisbon Council.
Edvinsson, L., & Malone, M. S. (1997). Intellectual Capital: Realizing Your Company\'s True Value by Finding Its Hidden Brainpower.
El-Bannany, M. (2008). A study of determinants of intellectual capital performance in banks: the UK case. *Journal of Intellectual Capital, 9*(3), 487-498.
Firer, S., & Williams, S. M. (2003). Intellectual capital and traditional measures of corporate performance. *Journal of Intellectual Capital, 4*(3), 348-360.
Florin, J., Lubatkin, M., & Schulze, W. (2002). A social capital model of high growth ventures. *Academy of Management Journal, 46*, 374-384.
Foray, D. (2006). *Optimizing the use of knowledge*. Retrieved from
Frederickson, J. R., Webster, E., & Williamson, I. O. (2010). Is the Current Accounting Treatment of Education and Training Costs Appropriate? *Australian Accounting Review, 20*(3), 265-273.
Gan, K., & Saleh, Z. (2008). Intellectual capital and corporate performance of technology-intensive companies: Malaysia evidence. *Asian journal of business and Accounting, 1*(1), 113-130.
Garcia-Parra, M., Simo, P., Sallan, J. M., & Mundet, J. (2009). Intangible liabilities: beyond models of intellectual assets. *Management Decision, 47*(5), 819-830.
Gigante, G. (2013). Intellectual Capital and Bank Performance in Europe. *Accounting and Finance Research, 2*(4), p120.
Glen, J., Lee, K., & Singh, A. (2001). Persistence of profitability and competition in emerging markets. *Economics Letters, 72*(2), 247-253.
Goh. (2003). Improving organizational learning capability: lessons from two case studies. *The learning organization, 10*(4), 216-227.
Grant, R. M. (1996). Toward a Knowledge-Based Theory of the firm. *Strategic management journal, 17*(S2), 109-122.

Gujarati, D. N. (2012). *Basic econometrics*: Tata McGraw-Hill Education.
Gupta, O., & Roos, G. (2001). Mergers and acquisitions through an intellectual capital perspective. *Journal of Intellectual Capital, 2*(3), 297-309.
Guthrie, J. (2001). The management, measurement and the reporting of intellectual capital. *Journal of Intellectual Capital, 2*(1), 27-41.
Guthrie, J., & Petty, R. (2000). Intellectual capital: Australian annual reporting practices. *Journal of Intellectual Capital, 1*(3), 241-251.
Guthrie, J., Ricceri, F., & Dumay, J. (2012). Reflections and projections: a decade of intellectual capital accounting research. *The British Accounting Review, 44*(2), 68-82.
Hall, B., & Van Reenen, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence. *Research policy, 29*(4), 449-469.
Hansen, L. P., & Singleton, K. J. (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica: Journal of the Econometric Society*, 1269-1286.
Harmantzis, F., & Tanguturi, V. P. (2005). Key determinants of R&D expenditures in the US telecommunications equipment industry. *Available at SSRN 686968*.
Harrison, S., & Sullivan Sr, P. H. (2000). Profiting from intellectual capital: learning from leading companies. *Journal of Intellectual Capital, 1*(1), 33-46.
Hiebeler, R. J. (1996). Benchmarking: knowledge management. *Planning Review, 24*(2), 22-29.
Ho, C.-A., & Williams, S. M. (2003). International comparative analysis of the association between board structure and the efficiency of value added by a firm from its physical capital and intellectual capital resources. *The International Journal of Accounting, 38*(4), 465-491.
Hobley, S., & Kerrin, M. (2004). MEASURING PROGRESS AT THE FRONT LINE Auditing initiatives that measure how people use the knowledge resources available to them in the workplace. *Knowledge Management Review, 7*, 12-15.
Hormiga, E., Batista-Canino, R. M., & Sánchez-Medina, A. (2011). The role of intellectual capital in the success of new ventures. *International Entrepreneurship and Management Journal, 7*(1), 71-92.
Hsu, L. C., & Wang, C. H. (2012). Clarifying the effect of intellectual capital on performance: the mediating role of dynamic capability. *British Journal of Management, 23*(2), 179-205.
Huang, C. C. (2007). *Accounting for intellectual capital: Internal and external reporting.* Universiti Teknologi Mara.
Inkinen, H. T., & Chase, R. (2015). Review of Empirical Research on Intellectual Capital and Firm Performance. *Journal of Intellectual Capital, 16*(3).
Itami, H., & Roehl, T. W. (1991). *Mobilizing invisible assets*: Harvard University Press.
Jhunjhunwala, S. (2009). Monitoring and measuring intangibles using value maps: some examples. *Journal of Intellectual Capital, 10*(2), 211-223.
Joia, L. A. (2000). Measuring intangible corporate assets: linking business strategy with intellectual capital. *Journal of Intellectual Capital, 1*(1), 68-84.
Joshi, M., Cahill, D., & Sidhu, J. (2010). Intellectual capital performance in the banking sector: An assessment of Australian owned banks. *Journal of Human Resource Costing & Accounting, 14*(2), 151-170.
Joshi, M., Cahill, D., Sidhu, J., & Kansal, M. (2013). Intellectual capital and financial performance: an evaluation of the Australian financial sector. *Journal of Intellectual Capital, 14*(2), 264-285.
Kai, W. C. S., Hang Chan, K., & Wu, W. W. (2011). Charting intellectual capital performance of the gateway to China. *Journal of Intellectual Capital, 12*(2), 249-276.
Kamal, M. H. M., Mat, R. C., Rahim, N. A., Husin, N., & Ismail, I. (2012). Intellectual capital and firm performance of commercial banks in Malaysia. *Asian Economic and Financial Review, 2*(4), 577-590.
Kannan, G., & Aulbur, W. G. (2004). Intellectual capital: measurement effectiveness. *Journal of Intellectual Capital, 5*(3), 389-413.
Kaplan, R. S., & Norton, D. P. (1995). Putting the balanced scorecard to work. *Performance measurement, management, and appraisal sourcebook, 66*, 17511.
Kaplan, R. S., & Norton, D. P. (2004). Measuring the strategic readiness of intangible assets. *Harvard Business Review, 82*(2), 52-63.

Karatepe, O. M., & Uludag, O. (2008). Role stress, burnout and their effects on frontline hotel employees' job performance: evidence from Northern Cyprus. *International Journal of Tourism Research, 10*(2), 111-126.

Knight, D. J. (1999). Performance measures for increasing intellectual capital. *Strategy & leadership, 27*(2), 22-27.

Kolachi, N. A., & Shah, H. A. (2013). BRICS countries and their strategic HRD agenda in 2020. *International Journal of Management & Information Systems (IJMIS), 17*(2), 105-112.

Koller, T., Goedhart, M., & Wessels, D. (2010). *Valuation: measuring and managing the value of companies* (Vol. 499): john Wiley and sons.

Kwan, S. H. (2003). Operating performance of banks among Asian economies: An international and time series comparison. *Journal of Banking & Finance, 27*(3), 471-489.

Kweh, Q. L., Chan, Y. C., & Ting, I. W. K. (2013). Measuring intellectual capital efficiency in the Malaysian software sector. *Journal of Intellectual Capital, 14*(2), 310-324.

Leslie, M., & Holloway, C. A. (2006). The sales learing curve. *Harvard Business Review, (July-August)*, 115–123.

Lev, B. (2000). *Intangibles: Management, measurement, and reporting*: Brookings Institution Press.

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of accounting and economics, 21*(1), 107-138.

Li, J., Mangena, M., & Pike, R. (2012). The effect of audit committee characteristics on intellectual capital disclosure. *The British Accounting Review, 44*(2), 98-110.

Lin, C. Y.-Y., Edvinsson, L., Chen, J., & Beding, T. (2012). *National Intellectual Capital and the Financial Crisis in China, Hong Kong, Singapore, and Taiwan* (Vol. 8): Springer.

Lu, W.-M., Wang, W.-K., & Kweh, Q. L. (2014). Intellectual capital and performance in the Chinese life insurance industry. *Omega, 42*(1), 65-74.

Luthans, F., & Youssef, C. M. (2004). Human, Social, and Now Positive Psychological Capital Management:: Investing in People for Competitive Advantage. *Organizational dynamics, 33*(2), 143-160.

Luthy, D. H. (1998). *Intellectual capital and its measurement.* Paper presented at the Proceedings of the Asian Pacific Interdisciplinary Research in Accounting Conference (APIRA), Osaka, Japan.

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and statistics, 61*(S1), 631-652.

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

Marr, B., Pike, S., Fernström, L., & Roos, G. (2005). Intellectual capital: Management approach in ICS Ltd. *Journal of Intellectual Capital, 6*(4), 489-509.

Martínez-Torres, M. R. (2006). A procedure to design a structural and measurement model of intellectual capital: an exploratory study. *Information & Management, 43*(5), 617-626.

Mavridis, D. G. (2004). The intellectual capital performance of the Japanese banking sector. *Journal of Intellectual Capital, 5*(1), 92-115.

Mehralian, G., Rajabzadeh, A., Reza Sadeh, M., & Reza Rasekh, H. (2012). Intellectual capital and corporate performance in Iranian pharmaceutical industry. *Journal of Intellectual Capital, 13*(1), 138-158.

Menor, L. J., Kristal, M. M., & Rosenzweig, E. D. (2007). Examining the influence of operational intellectual capital on capabilities and performance. *Manufacturing & Service Operations Management, 9*(4), 559-578.

Moeller, K. (2009). Intangible and financial performance: causes and effects. *Journal of Intellectual Capital, 10*(2), 224-245.

Mouritsen, J., Bukh, P. N., & Bang, H. K. (2005). Understanding Intellectual Capital in an Innovative Medium-sized Firm: The Case Of Maxon Telecom. *Australian Accounting Review, 15*(36), 30-39.

Muhammad, N. M. N., & Ismail, M. K. A. (2009). Intellectual capital efficiency and firm's performance: study on Malaysian financial sectors. *International Journal of Economics and Finance, 1*(2), 206.

Mulkay, B., Hall, B. H., & Mairesse, J. (2001). *Firm level investment and R&D in France and the United States: A comparison*: Springer.
Murthy, V., & Mouritsen, J. (2011). The performance of intellectual capital: mobilising relationships between intellectual and financial capital in a bank. *Accounting, Auditing & Accountability Journal, 24*(5), 622-646.
Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics, 13*(2), 187-221.
Nahapiet, J., & Ghoshal, S. (1997). *SOCIAL CAPITAL, INTELLECTUAL CAPITAL AND THE CREATION OF VALUE IN FIRMS.* Paper presented at the Academy of Management Proceedings.
Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of management Review, 23*(2), 242-266.
Navarro, A., Luis, J., & Lopez Ruiz, V. R. (2011). *Estimation of intellectual capital in the European Union using a knowledge model.* Paper presented at the Proceedings of Rijeka Faculty of Economics, Journal of Economics and Business.
Nguyen, T., Locke, S., & Reddy, K. (2015). Does boardroom gender diversity matter? Evidence from a transitional economy. *International Review of Economics & Finance, 37*, 184-202.
Nikolaj, B. P., Nielsen, C., Gormsen, P., & Mouritsen, J. (2005). Disclosure of information on intellectual capital in Danish IPO prospectuses. *Accounting, Auditing & Accountability Journal, 18*(6), 713-732.
Nimtrakoon, S., & Chase, R. (2015). The Relationship between Intellectual Capital, Firms' Market Value and Financial Performance: Empirical Evidence from the ASEAN. *Journal of Intellectual Capital, 16*(3).
Njuguna, J. I. (2009). Strategic positioning for sustainable competitive advantage: an organizational learning approach. *KCA Journal of Business Management, 2*(1).
Nonaka, I. (1991). The knowledge-creating company. *Harvard Business Review, 69*(6), 96-104.
Nonaka, I., & Takeuchi, H. (1997). The knowledge-creating company. *1995*.
O'Donnell, D., Porter, G., McGuire, D., Garavan, T. N., Heffernan, M., & Cleary, P. (2003). Creating intellectual capital: a Habermasian community of practice (CoP) introduction. *Journal of European Industrial Training, 27*(2/3/4), 80-87.
O'Donnell, D., Porter, G., McGuire, D., Garavan, T. N., Heffernan, M., & Cleary, P. (2003). Creating intellectual capital: a Habermasian community of practice (CoP) introduction. *Journal of European Industrial Training, 27*(2/3/4), 80-87.
OECD. (1996). The Knowledge Based Economy. *Organisation for Economic Co-operation and Development (OECD)*. Retrieved from
Ohlson, J. A. (1995). Earnings, book values, and dividends in equity valuation*. *Contemporary accounting research, 11*(2), 661-687.
Ordóñez de Pablos, P. (2003). Intellectual capital reporting in Spain: a comparative view. *Journal of Intellectual Capital, 4*(1), 61-81.
Osborne, J. (2005). Notes on the use of data transformations. *Practical Assessment, Research and Evaluation, 9*, 42-50.
Pal, K., & Soriya, S. (2012). IC performance of Indian pharmaceutical and textile industry. *Journal of Intellectual Capital, 13*(1), 120-137.
Pantzalis, C., & Park, J. C. (2009). Equity market valuation of human capital and stock returns. *Journal of Banking & Finance, 33*(9), 1610-1623.
Pedrini, M. (2007). Human capital convergences in intellectual capital and sustainability reports. *Journal of Intellectual Capital, 8*(2), 346-366.
Pek, C. G. (2005). Intellectual capital performance of commercial banks in Malaysia. *Journal of Intellectual Capital, 6*(3), 385-396.
Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic management journal, 14*(3), 179-191.
Petty, R., & Guthrie, J. (2000). Intellectual capital literature review: measurement, reporting and management. *Journal of Intellectual Capital, 1*(2), 155-176.
Pfeffer, J., & Salancik, G. R. (2003). *The external control of organizations: A resource dependence perspective*: Stanford University Press.

Pulic, A. (1998). *Measuring the performance of intellectual potential in knowledge economy.* Paper presented at the 2nd McMaster Word Congress on Measuring and Managing Intellectual Capital by the Austrian Team for Intellectual Potential.
Pulic, A. (2004). Intellectual capital–does it create or destroy value? *Measuring business excellence, 8*(1), 62-68.
Rangone, A. (1997). Linking organizational effectiveness, key success factors and performance measures: an analytical framework. *Management Accounting Research, 8*(2), 207-219.
Rastogi, P. (2003). The nature and role of IC: Rethinking the process of value creation and sustained enterprise growth. *Journal of Intellectual Capital, 4*(2), 227-248.
Razafindrambinina, D., & Anggreni, T. (2008). *An Empirical Research on the Relationship between Intellectual Capital and Corporate Financial Performance on Indonesian Listed Companies.* Paper presented at the 2008 年国际会计与商业会议论文集.
Reed, K. K., Lubatkin, M., & Srinivasan, N. (2006). Proposing and testing an intellectual capital-based view of the firm. *Journal of Management Studies, 43*(4), 867-893.
Rehman, W., Rehman, C. A., Rehman, H., & Zahid, A. (2011). Intellectual capital performance and its impact on corporate performance: an empirical evidence from Modaraba sector of Pakistan. *Australian journal of business and management research, 1*(5), 08-16.
Romijn, H., & Albaladejo, M. (2002). Determinants of innovation capability in small electronics and software firms in southeast England. *Research policy, 31*(7), 1053-1067.
Roodman, D. (2006). How to do xtabond2: An introduction to difference and system GMM in Stata. *Center for Global Development working paper*(103).
Roos, J., Edvinsson, L., & Roos, G. (1997). *Intellectual capital: Navigating in the new business landscape*: New York University Press.
Ross, S. A., Westerfield, R., & Jordan, B. D. (2008). *Fundamentals of corporate finance*: Tata McGraw-Hill Education.
Sakakibara, S., Hansson, B., Yosano, T., & Kozumi, H. (2010). Analysts' perceptions of intellectual capital information. *Australian Accounting Review, 20*(3), 274-285.
Salamudin, N., Bakar, R., Kamil Ibrahim, M., & Haji Hassan, F. (2010). Intangible assets valuation in the Malaysian capital market. *Journal of Intellectual Capital, 11*(3), 391-405.
Şamiloğlu, F. (2006). THE PERFORMANCE ANALYSIS OF THE TURKISH BANKS THROUGH VAIC TM AND MV/BV RATIO. *Çanakkale Onsekiz Mart Üniversitesi, Biga İİ BF Yönetim Bilimleri Dergisi, 4*(1).
Schneider, U. (1998). *The Austrian approach to the measurement of intellectual potential.* Paper presented at the National Business Conference, Hamilton.
Serena Chiucchi, M. (2013). Measuring and reporting intellectual capital: Lessons learnt from some interventionist research projects. *Journal of Intellectual Capital, 14*(3), 395-413.
Shah, A. (2006). Fiscal incentives for investment and innovation. *Available at SSRN 896144*.
Sharabati, A.-A. A., Naji Jawad, S., & Bontis, N. (2010). Intellectual capital and business performance in the pharmaceutical sector of Jordan. *Management Decision, 48*(1), 105-131.
Shiu, H.-J. (2006). The Application of the Value Added Intellectual Coefficient to Measure Corporate Performance: Evidence from Technological Firms. *International Journal of Management, 23*(2).
Spender, J. C., & Grant, R. M. (1996). Knowledge and the firm: overview. *Strategic management journal, 17*(S2), 5-9.
Ståhle, P., & Bounfour, A. (2008). Understanding dynamics of intellectual capital of nations. *Journal of Intellectual Capital, 9*(2), 164-177.
Ståhle, P., Ståhle, S., & Aho, S. (2011). Value added intellectual coefficient (VAIC): a critical analysis. *Journal of Intellectual Capital, 12*(4), 531-551.
Stewart, & Ruckdeschel, C. (1998). Intellectual capital: The new wealth of organizations: Wiley Online Library.
Stewart, T. A. (2007). *The wealth of knowledge: Intellectual capital and the twenty-first century organization*: Random House LLC.
Su, H.-Y. (2014). Business ethics and the development of intellectual capital. *Journal of Business Ethics, 119*(1), 87-98.

Su, W. H., & Wells, P. (2015). The association of identifiable intangible assets acquired and recognised in business acquisitions with postacquisition firm performance. *Accounting & Finance, 55*(4), 1171-1199.

Subramaniam, M., & Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal, 48*, 450-463.

Sujan, A., & Abeysekera, I. (2007). Intellectual capital reporting practices of the top Australian firms. *Australian Accounting Review, 17*(42), 71-83.

Sumedrea, S. (2013). Intellectual Capital and Firm Performance: A Dynamic Relationship in Crisis Time. *Procedia Economics and Finance, 6*, 137-144.

Sveiby, K. E. (1997). *The new organizational wealth: Managing & measuring knowledge-based assets*: Berrett-Koehler Publishers.

Sydler, R., Haefliger, S., & Pruksa, R. (2014). Measuring intellectual capital with financial figures: Can we predict firm profitability? *European Management Journal, 32*(2), 244-259.

Tan, H. P., Plowman, D., & Hancock, P. (2007). Intellectual capital and financial returns of companies. *Journal of Intellectual Capital, 8*(1), 76-95.

Tan, H. P., Plowman, D., & Hancock, P. (2008). The evolving research on intellectual capital. *Journal of Intellectual Capital, 9*(4), 585-608.

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

Tomo, O. (2010). Ocean Tomo's Intangible Asset Market Value Study. *Ocean Tomo Announces Result of Annual Study of Intangible Asset Market Value*.

Ulum, I., Ghozali, I., & Purwanto, A. (2014). Intellectual Capital Performance of Indonesian Banking Sector: A Modified VAIC (M-VAIC) Perspective. *Asian Journal of Finance & Accounting, 6*(2), 103-123.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of marketing, 68*(1), 1-17.

Vergauwen, P., Bollen, L., & Oirbans, E. (2007). Intellectual capital disclosure and intangible value drivers: an empirical study. *Management Decision, 45*(7), 1163-1180.

Vishnu, S., & Kumar Gupta, V. (2014). Intellectual capital and performance of pharmaceutical firms in India. *Journal of Intellectual Capital, 15*(1), 83-99.

Wang, W.-Y., & Chang, C. (2005). Intellectual capital and performance in causal models: evidence from the information technology industry in Taiwan. *Journal of Intellectual Capital, 6*(2), 222-236.

Widener, S. K. (2006). Human capital, pay structure, and the use of performance measures in bonus compensation. *Management Accounting Research, 17*(2), 198-221.

Williams, M. (2000). *Is a company's intellectual capital performance and intellectual capital disclosure practices related? Evidence from publicly listed companies from the FTSE 100.* Paper presented at the borrador presentado en McMasters Intellectual Capital Conference, enero, Toronto.

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of Financial Economics, 105*(3), 581-606.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*: The MIT Press, Cambridge

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT press.

Wright, P. M., McMahan, G. C., & McWilliams, A. (1994). Human resources and sustained competitive advantage: a resource-based perspective. *International journal of human resource management, 5*(2), 301-326.

Yalama, A., & Coskun, M. (2007). Intellectual capital performance of quoted banks on the Istanbul stock exchange market. *Journal of Intellectual Capital, 8*(2), 256-271.

Youndt, M. A., Subramaniam, M., & Snell, S. A. (2004). Intellectual Capital Profiles: An Examination of Investments and Returns*. *Journal of Management Studies, 41*(2), 335-361.

Young, C.-S., Su, H.-Y., Fang, S.-C., & Fang, S.-R. (2009). Cross-country comparison of intellectual capital performance of commercial banks in Asian economies. *The Service Industries Journal, 29*(11), 1565-1579.

Zambon, S. (2004). Intangibles and intellectual capital: an overview of the reporting issues and some measurement models. *The Economic Importance of Intangible Assets*, 153-183.
Zangoueinezhad, A., & Moshabaki, A. (2009). The role of structural capital on competitive intelligence. *Industrial Management & Data Systems, 109*(2), 262-280.
Zéghal, D., & Maaloul, A. (2010). Analysing value added as an indicator of intellectual capital and its consequences on company performance. *Journal of Intellectual Capital, 11*(1), 39-60.
Zerenler, M., Hasiloglu, S. B., & Sezgin, M. (2008). Intellectual capital and innovation performance: Empirical evidence in the Turkish automotive supplier. *Journal of technology management & innovation, 3*(4), 31-40.