Erasmus
School of
Economics

The Effects of Intellectual Capital on S&P 500 Firm Performance

Master Thesis: Strategy Economics

Laurens Braas

450403

Supervisor: dr. SJA Hessels

Second Assessor: dr. AS Bhaskarabhatla

This version: October 20, 2022

Abstract: In this research, the effect of intellectual capital on firm performance is studied. Previous studies have indicated that it is difficult to quantify, but that it generally has a positive effect on firm performance. To verify whether this is true, and how future performance is affected, this research analyses S&P 500 firms from 2000 – 2015. It was found that intellectual capital, and its three main components: human, organisational, and social capital, have generally positive relationships with different measures of firm performance. In doing so, human capital was found to be the most significant factor. Though intellectual capital improves current performance, it was found that it only partially improves future performance, implying that it can lead to short-term advantages, but that these are less certain in the long-run.

Keywords: Intellectual capital, Tobin's q, knowledge economy

JEL codes: E22, G32, L25, O3

TABLE OF CONTENTS

1. INTRODUCTION

The contemporary economic system is one that is increasingly based on intellectual capital and intangible assets. As a result of a decrease in the reliance on factor accumulation coupled with the rise of intangibles, the idea of a *knowledge economy* was popularised by Peter Drucker (1969). Chen and Dahlman (2006) define the knowledge economy to be, in essence, an economy where economic growth is spearheaded by knowledge, which encompasses innovation, technological adoption, and conducive environments in which growth is achieved through technological progress and understanding. In this paper, the knowledge economy phenomenon will be investigated in the light of the performance of firms in the Standard and Poor's 500 (hereafter: S&P 500) stock market index. In doing so, its primary components will be examined and their effects on firm performance will be empirically tested and discussed.

As mentioned before, the knowledge economy is characterised by intangible assets, which are assets lacking a physical presence. Specifically, it is part of *intellectual capital*, which Brooking (1996) defines as the term given to the combined intangible assets which allow a company to function. According to Stewart (1995) this includes an organisation's process optimisation, technology, patents, ability, skill, and information. Intellectual capital is notoriously hard to quantify, however there are multiple methods that attempt this. Megna and Klock (1993) suggest that assessing Tobin's q is one of the methods to measure it. Blanchard (2010) defines Tobin's q to be the ratio of the value of capital stock relative to its current valuation. First introduced by Kaldor (1966) as the ratio between a firm's market value of physical assets and its replacement value, it was subsequently popularised by Tobin (1969), who further explored its role in monetary policy. In the following decade, it was widely adopted and henceforth became known as Tobin's q. In the context of intellectual capital, it can serve the function of indicating whether a company is overvalued. If this is the case, the overvaluation stems from intangible capital. For instance, Tesla is notorious for being valued higher than established industry counterparts, even though the firm owns substantially less assets. Consequently, they feature a higher value for q reflecting their worth as an innovative company.

To give insight into the workings of the knowledge economy, and hence illustrate what intellectual capital is comprised of, Lundvall and Johnson (1994) wrote a seminal paper in which they made a distinction between four different types of knowledge. Firstly, *know-what* refers to knowledge about factual information. Secondly, *know-why* refers to knowledge about how and why processes occur and function. Thirdly, *know-how* is a measure of capability, or knowledge of how to do specific things. Fourth, *know-who* refers to social skills, or more applicably, the strength of one's social network. These four pillars of the knowledge economy are the driving forces behind identifying intellectual capital and determining its specific components. The components translate into three main categories: human capital (know-how and know-why), organisational capital (know-what), and social capital (know-who).

The current research will consider the effects of intellectual capital and its components, human, organisational, and social capital, on firms in the S&P 500 stock market index, which keeps track of the performance of the 500 largest companies (by market capitalisation) in the United States. This paper is guided by a central research question, namely:

"How does intellectual capital influence firm performance in the S&P 500?"

These companies are well-documented and public, meaning that there is an abundance of publicly available data. This is particularly important for some variables for which obtaining data is difficult. This includes things like patent stock or factors related to intrafirm functioning. In addition, companies in the S&P 500 are widely used as benchmarks for the performance of the economy, particularly that of the United States, alleviating some external validity issues (Beers, 2022). As such, the results from researching intellectual capital in the context of the S&P 500 can be applied to other firms and industries around the world. The timeframe of this study is annual data from the fiscal years of 2000 – 2015, placing it post-advent of ICT but including several fluctuations and economic downturns. The dataset was compiled from several sources, but primarily from Compustat North America's annual fundamental financial information, which provides key financial metrics for S&P 500 firms. Firm performance was quantified by several indicators, namely: return on equity (RoE), return on assets

(RoA), and revenue growth (RG). Meanwhile, *q* was used as a proxy to indicate the presence of intellectual capital, whereas several variables were identified and utilised to measure the specific components of intellectual capital.

The current thesis contributes to the research on intellectual capital by providing more information on its relationship with firm performance, both in the present and in the future. This paper makes a distinction between current and future performance, highlighting that intellectual capital affects these differently. As it stands, the literature suggests that there is a positive relationship between firm performance and intellectual capital, however, intellectual capital is usually measured by a specific indicator rather than a broader view. This research adds to the literature by coalescing prior research on intellectual capital to determine its specific components. This allows the testing on relative importance of human, organisational, and social capital, specifically how they interact with each other, and how these factors differ across industries. Finding answers to component specific issues is particularly interesting, as this is an area of research that is rarely (if ever) studied in the literature. As a result, the findings of this research could significantly improve the understanding of the definition of intellectual capital, its measurement, and the relative importance of its components. The answers to the research question and hypotheses may have important implications for investors and policymakers alike, who can adjust their strategies to more accurately reflect the inclusion of intellectual capital.

Based on the research question and the theoretical background, several hypotheses are deduced for empirical testing. Subsequently, these are analysed by using a two-step system GMM model. The hypotheses postulate that there is a positive relation between intellectual capital and firm performance, both in the present and the future, as measured by RoA, RoE, and revenue growth. Furthermore, several component-specific ideas were explored; it was surmised that organisational capital has a relatively greater effect on firm performance than other components. The results of the research indicate that, as the theoretical background suggested, intellectual capital is hard to quantify. However, it was found that firm performance is generally positively affected by intellectual capital. More specifically, human capital was found to be the most significant factor in this effect. Though it was concluded that intellectual capital improves current firm performance, it was found that it only partially affects the future performance of a firm. Whilst it does not have a completely positive relationship with firm performance in the future, several component-specific indicators did.

This paper will commence by reviewing previous research performed on the advent of intellectual capital in the literature, its components, and the different methods to measure it. Next, the research hypotheses are devised based on the research question and the findings from the theoretical background. This is followed by the specification and explanation of the research methodology. After the model and data have been established, the results will be presented. Finally, the results will be analysed and discussed, followed by the conclusion of the paper.

2. LITERATURE REVIEW

2.1 Historical Perspectives on Intellectual Capital

The notion that knowledge, and as such intellectual capital, has a significant role in determining overall assets has only been established relatively recently in the field of economics. The cornerstones in shaping economic thought, such as Adam Smith in his 1776 epoch, all regarded tangible assets as produced by labour inputs to be the only capital that one could use and accumulate. Subsequently, it took another century until the idea was furthered by Marshall (1890), who recognised that next to classic factors of production (i.e. labour and land), immaterial goods should also be included in calculating total assets. However, immaterial goods were only viewed as minor additions to the primary factors of production being acquired as a part of tangible capital. This view persisted for almost a century afterwards.

Following Marshall's work, technological progress (i.e. knowledge) was widely regarded as a given factor in a market, albeit at different levels depending on the market. Engelbrecht (2003) states that the perspective was that knowledge was captured in the 'state of knowledge' and that it was exogenously acquired by all firms within a market. Still, it was included in theories at the time such as Solow (1956), who theorised that economic growth is a function of output and capital per worker, but that aggregate output could increase if the given rate of technology increases. Moreover, Solow (1957) was one of the precursors in calculating intangible assets by composing an estimate of technological progress by looking at the share of economic growth that is not explained by accumulating factors of production. However, even papers based on his findings did not consider knowledge accumulation. A prevalent example is Nelson (1959), who studies the economics of inventions. Though he does discuss the effects of uncertainty, which itself is intangible, the effect of knowledge is still underrepresented, and inventions are seen as an improvement of the state of knowledge and technology as a result of a successful culmination of knowledge build-up. Yet this build-up is deemed worthless until it results in an invention, hence the aforementioned uncertainty.

Even in the 1960s, knowledge was still not widely regarded as an important factor in determining value through its accumulation. One of the first to identify knowledge as an endogenous variable instead of an exogenous variable, as per the previous examples, was Arrow (1962). He stated that knowledge was not merely a given state, but that the production function could shift upwards by 'learning', which essentially refers to acquiring knowledge. This argument was furthered by Boulding (1966), who pointed towards considering knowledge as a measurable commodity that can give advantages when accumulated. Subsequently, he reiterates that the difficulties in measuring knowledge leads to a neglect of recognising it as a commodity, even in economic theory itself. Furthermore, as mentioned in the introduction, around this time Drucker (1969) recognised a decrease in reliance on factor accumulation and the rising importance of intangible assets, leading to the coinage of the knowledge economy.

According to Corrado et al. (2006), it took until the 1980s before intangible assets were incorporated in calculating economic variables. In addition, they find that from this point, intangible investment has grown considerably more rapidly than tangible business investment. This period was hallmarked by several seminal papers, such as Romer (1986), who introduced knowledge accumulation to models as a driver of endogenous technological change instead of exogenous 'states' of technology. Moreover, he recognised it as having diminishing returns and spill-over effects for other firms. In Romer (1989), he extended the model by providing additional theory and evidence, but crucially does not perform a quantitative analysis. Since then, Webster and Jensen (2006) recognise that significant advances have been made in its recognition as an important variable, its definition and composition (e.g. Lundvall and Johnson, 1994), and the ways to measure it. Following, the next subsections will focus on its definition and explore different methodologies used to gauge intellectual capital.

2.2 Defining Intellectual Capital

As described before, intellectual capital has gained considerable attention in the literature. However, Edvinsson (1996) and Hunter et al. (2005) state that the writing on its exact description or definition is inadequate. Different descriptions of the term have been offered by different authors. Most prominently, Brooking (1996) defines it as combined intangible assets consisting of market, intellectual property, human-centred and infrastructure which enable the company to function. This could include brand image, patents, employee skills, access to databases, etc. Moreover, Stewart (1995) writes that this includes an organisation's process optimisation, technology, patents, ability, skill, and information. Somewhat more succinctly, he phrases it as 'packaged useful knowledge' due to these individual elements improving firm performance. Furthermore, one of the frontrunners of companies adopting intellectual capital in their business model is Skandia (1996), which defined it as the accumulated value of investments in employee training, competence, and the future. Lastly, Pablos (2003) mentions that it consists of resources created by internal learning and the development of valuable relationships. Moreover, akin to the measurement methods discussed later, he states that it is the difference between a company's market value and its book value.

For the purposes of the current research, the previous descriptions are combined into a single definition based on Lundvall and Johnson's (1994) four knowledge types. Accordingly, intellectual capital is defined as all value-adding intangible assets that a company relies on to function. They fall into three broad categories that will be developed later in this section, namely: human capital, organisational capital, and social capital.

2.3 Measuring Intellectual Capital

Much like defining intellectual capital, measuring it can also be elusive. Youndt et al. (2004) state that it suffers from the dilemma of being theoretically interesting, but extremely hard to identify and measure. In fact, it took until the late 1990s until several researchers started to prepare frameworks to conceptualise intellectual capital, thereby aiding the ability to quantify it. From that point onwards, numerous different methods have been developed to measure intellectual capital, starting with qualitative approaches and culminating in quantitative models. Among others, Levy and Duffey (2007) review a selection of different methods to assign a value to intellectual capital. They state that, as of yet, no method of quantifying intangible assets has proven superior to others. They continue by discussing the advantages and disadvantages of several prominent techniques, and like other similar papers, they fail to deduce which method is most suitable. Sitar and Vasić (2005) note that this is due to a lack of a general method to quantify intangibles, and that the different measurement methods are prone to error due to their difficulty to implement.

In the literature, the measurement of intellectual capital commenced with several qualitative measures. Subsequently, quantitative methods were developed based on the insights generated by the qualitative models. This resulted in three main methods to quantitatively evaluate intellectual capital becoming generally accepted. Levy and Duffey (2007) identify these to be cost-based, market-based, and income-based approaches. Firstly, they explain that the cost-based approach is primarily practiced by accountants and is based on reporting on the cost of developing intangible assets by looking at their value minus depreciation. Though this is a viable valuation technique for fixed assets, it is harder to evaluate dynamic assets. As the value that intellectual capital adds after its development is uncertain, this method might be insufficient. Secondly, the market-based approach is one that values intellectual capital by comparing it to other assets and firms. As Andriessen and Tissen (2001) state, it relies on competition and equilibrium effects to determine a fitting value for intellectual capital. In essence, it provides a valuation by comparing and contrasting firms and assets to each other. Thirdly, the income-based approaches are forward-looking and are an attempt at valuation based on expected future earnings. By using metrics such as cost of capital, these methods attempt to value intellectual capital by considering future potential.

2.4 Tobin's q

As indicated in the introduction, Tobin's q (hereafter: *q*) has risen to prominence as an investment tool to gauge whether investing in a firm is a viable option. Hayashi (1982) incorporated *q* into the *q*-theory of investment, which attempts to perfectly summarise the investment opportunities that a firm has. Since then, it has become one of the most well-known functions in corporate finance. Presently, it is still widely used and researched, for example by Piketty (2014), who illustrated a codependent relation between *q* and gross capital formation, adding to its relevance as an investment regressor.

Although the use of q in investment research was originally designed to account for physical investment, Peters and Taylor (2017) state that, without significant alterations, it also helps to explain intangible investment. Bo (1999) identifies that this occurs due to the q-theory of investment taking into account all factors, which includes different aspects of uncertainty. Specifically, it takes into account expected future profitability, thereby including uncertainty and, crucially, intellectual capital into the equation. This is confirmed by Bontis (1998), who gives an example of q-values for software and steel industries. He mentions that companies in the software industry, characterised by an abundance in intellectual capital, can feature q ratios of 7, versus a q of around 1 for steel industries, featuring large capital assets.

The viability of using q in accounting for intellectual capital is disputed, however. Levy and Duffey (2007) analyse its use in intellectual capital valuation and state that for it to be a proper measure, its over- or undervaluation must be attributable solely to intangible assets. Therefore, they deduce that q is not a completely appropriate measure, as there are many exogenous factors that affect market value, and there are many ways to estimate replacement value. As such, to be a relevant method to measure intellectual capital, either the effects of intellectual capital must be isolated or it must be used as a proxy for intellectual capital, rather than measuring it exactly. Peters and Taylor (2017) advocate for the latter approach. They review recent literature in which q is used as a proxy for intellectual capital and find that the explanatory power of the model is indeed lower if tangible and intangible assets are indistinguishable. Consequently, they devise a model that differentiates between tangible and intangible assets, similar to the model which will be used in the current research and elaborated upon in Section 4.

2.5 Categorising Intellectual Capital

In their seminal work, Lundvall and Johnson (1994) distinguished between four different types of knowledge. In the intellectual capital literature, Youndt et al. (2004) find that these translate into three main categories: human capital (know-how and know-why), organisational capital (know-what), and social capital (know-who). Following, these will be discussed in turn.

2.5.1 Human Capital

Human capital may be defined as quality of labour, with respect to productivity and capability (Weil 2013, p. 150). In essence, Barney (1991) states that it refers to the training, experience, judgement, intelligence, and insights of individuals within a firm. Goldin (2016) states that it can be improved through investments in people, such as education or training, and that these investments have a positive effect on individual productivity. Initially, research on human capital arose after Schultz' (1961) research, which illustrated its essential role in accounting for irregular economic phenomena. Moreover, he stressed that it is one of the primary firm resources and essential for a firm's success. However, the concept only really gained traction after Becker (1964), who stipulated that human capital is essential for economic development and reducing economic disparity. He identified investments in education and training as the primary drivers behind human capital and stated that this culminates in increased individual wages and wider firm performance.

Furthermore, one of the first to recognise the essential role of human capital for economic growth was Jacobs (1969; 1984). She researched the role of cities in economic growth and compared them to the nucleus of an atom; without anything holding a city together, it would fall apart. Without human capital consolidating the traditional factors of production in a single area, there is nothing that incentivises the existence of the city. Lastly, Lucas (1988) furthered understanding of the concept by highlighting its imperative role in stimulating economic development. He developed a model of economic growth, incorporating both physical and human capital, wherein human capital accumulation through education and learning-by-doing is vital.

Since its advent in research, human capital has become the most prominent form of intellectual capital. Subramanian and Youndt (2005) state that it is essential nowadays as it is the sum of employees' capacity to create tangible and intangible assets using their ideas and knowledge, thereby creating value for the organisation. Human capital has been linked to be one of the primary drivers of economic growth (Barro, 2001; Barney, 1991). It increases the rate at which domestic innovation is produced (Romer 1990) and also increases the rate at which a country may adapt to foreign technology (Nelson and Phelps 1966), which ultimately leads to an increase in economic growth. Crucially, human capital is inherent in people, meaning it cannot be owned by organisations and can leave an organisation as its workers exit (Luthy, 1998). Youndt et al. (2004) state that it can only be rented or borrowed, meaning that a firm can invest in it to acquire it through training or hiring talent.

2.5.2 Organisational Capital

Organisational capital refers to the knowledge embedded in a firm's processes, routines, and practices (Jansen et al., 2009). Hall (1992) notes that this includes knowledge at the institutional level, and codified information that is accounted for in databases, routines, manuals, structures, and intellectual property. Unlike human capital, Youndt et al. (2004) recognise that this is capital that the firm actually owns, meaning that it is inherent to an organisation and thus excludable. For example, patents that a company owns (referring to a type of intellectual property) are protected from misappropriation by legislature. Interestingly, organisational capital includes various items which are readily recognised on a company's balance sheet (Minovski and Jancevska, 2018). However, Hall et al. (2007) find that the real value of intellectual property is not reflected properly on balance sheets. Specifically, externally-generated intellectual property is mostly valued fairly, namely by using the cost of acquiring it, but internally-generated items can be over- or understated.

As mentioned previously, the types of intellectual capital are categorised based on Youndt et al. (2004), who synthesised the categories based on some of the more prominent strands of intellectual capital literature. Organisational capital is particularly disputed, falling under the moniker of structured capital (Stewart, 1995), infrastructure assets (Brooking, 1996), internal capital (Sveiby, 1997), and process capital (Edvinsson and Malone, 1997). As in Youndt et al. (2004), the distinctive feature of organisational capital is that it is owned by the firm, making its nomenclature more apt.

2.5.3 Social Capital

Social capital may be defined as the knowledge and resources that surround networks of people and are embedded in social groups (Nahapiet and Ghoshal, 1998). Whereas human capital resides at the individual level, and organisational capital at the firm level, Youndt et al. (2004) state that social capital is neither, and instead is an intermediary form of intellectual capital. Its roots stem from the sociology literature, where it was first conceptualised by Coleman (1988), who identified it as a catalyst for forming human capital, rather than acting as a standalone form of intellectual capital. Furthermore, Adler and Kwon (2002) coalesced the existing literature to narrow down to a definition for social capital. They examined the different actors between which social capital is formed and state that it is not limited to relationships within firms or between firms, but also extends to suppliers, partners, and critically, customers.

Like organisational capital, a specific part of social capital is recognised on balance sheets. The IFRS recognises goodwill as the surplus paid for acquiring a company compared to its balance sheet. Adler and Kwon (2002) define social capital to be the goodwill available to individuals or groups, yet this is not wholly accounted for by the goodwill item on a balance sheet. Bloom (2009) recognises that goodwill captures only purchased goodwill, and as with intellectual property, internally-generated goodwill cannot be accounted for within the accepted rules of bookkeeping. Thus, whilst a small portion of social capital can be captured on the balance sheet, it remains largely unaccounted for and intangible.

2.6 The Impact of Intellectual Capital on Firm Performance

Thus far, the advent, definition, measurement, and characteristics of intellectual capital have been discussed, but the actual impact of it has not been covered. Chen and Dahlman (2006) state that the modern economy has shifted towards a knowledge economy in which knowledge is the main source of economic growth. They elaborate that successful economic leaders feature continual economic growth through sustained use and creation of knowledge. Over the years, a plethora of researchers have made estimates of the total fraction of intangibles in the economy. Some of these approximations are more conservative, such as Corrado and Hulten (2010), who estimate that intangible capital makes up 34% of firms' total capital. Others are more ambitious, with Handy (1989) suggesting that intellectual assets of a corporation are usually three or four times tangible book value. Moreover, Corrado et al. (2006) state that macroeconomic data usually excludes intangible investment, leading to the omission of more than $3 trillion of business intangible capital stock in the United States.

Furthermore, Hejazi et al. (2016) summarise various strands of research on the effects of intellectual capital on firm performance, as measured by Tobin's *q*. They find that one of the primary effects of intellectual capital is that it augments innovative capabilities of a firm. In a study of Japanese firms, Kusunoki et al. (1998) find that innovative capabilities of firms are bolstered by the presence of knowledge assets. Furthermore, Chen et al. (2006) show that intellectual capital and its constituents are positively correlated with new product development. In addition, a plethora of different studies have researched the relationship between intellectual capital and firm performance, finding that there is a positive correlation between the two. For instance, Clarke et al. (2011) researched firms listed on the Australian Stock Exchange from 2003 to 2008 using return on assets (RoA), return on equity (RoE), revenue growth, and employee productivity as dependent variables. They found a direct positive relationship between these indicators for firm performance and intellectual capital. Moreover, Tan et al. (2007) found similar results for a sample of 150 Singaporean publicly listed firms within the years 2000 and 2002, as well as a positive correlation between intellectual capital and future firm performance.

Finally, these results are corroborated by firms in the United States as well, with research demonstrating a positive relationship between intellectual capital and business performance (Barney, 1991; Bontis 1998; Riahi-Belkaoui, 2003). Among others, Barney (1991) applied a model to gauge the feasibility of sustained competitive advantage in a firm, and found that intellectual capital was a key indicator. Furthermore, Bontis (1998) employed a survey approach to estimate the impact of intellectual capital on business performance. He found that there is a direct positive link between the two by considering a sample of MBA students employed across various different industries. Lastly, Riahi-Belkaoui (2003) also found a positive relationship between intellectual capital and firm performance in a sample of multinational manufacturing and service firms from 1992 to 1996. This was measured by assessing the effects of intellectual capital, as measured by patent and trademark generation, on value added to the firm.

2.6.1 Human Capital

Much like intellectual capital in general, the effect of human capital specifically has been subject to extensive research. One of the more prominent pieces of research in the field was conducted by Barney (1991), who researched the dynamics between unique firm resources and creating a sustained competitive advantage. He measured firm performance by considering competitive advantages, which he defines as strategies not employed by current or potential competitors. He found that human capital relates strongly to firm performance and can lead to a sustained advantage, provided that it is rare or hard to imitate. Moreover, similar results were found by Crook et al. (2011), who performed a meta-analysis of a plethora of studies on the human capital and firm performance relationship. They found that human capital has a positive effect on firm performance across the board, and that if it can be protected, this exacerbates the competitive edge. One of these ways is to promote firm-specific human capital, as this is harder to imitate by other firms as it is tailored to each individual firm. Next to this, firms can attempt to protect their human capital by creating incentives for employees to remain at the firm, for instance by salary increases or other benefits. Additionally, Pablos (2003) researched the existence and reporting on intangibles in Spain. In his research, he surveyed over 2000 firms in the manufacturing sector, and found that human capital is a vital piece of intellectual capital, stimulating firm efficiency and leading to a competitive advantage.

On another note, the role of human capital in fostering technological adoption has also been researched. According to Benhabib and Spiegel (1994), human capital not only enhances intrafirm ability to innovate, but also its absorptive capacity, which refers to its ability to adopt and implement technologies developed elsewhere. In fact, Galor (2004) found that as the distance from a technological frontier gets larger, the role of human capital becomes more significant in technological advancement. Allen (2012) corroborated these results, finding that for firms that do not pioneer innovations, human capital is integral in catching up to the pioneers. Hence, not only does human capital play a role in firm performance, it also serves as a catalyst for adopting superior innovations and technologies.

2.6.2 Organisational Capital

In the literature, organisational capital is suggested to contribute to firm performance in two main ways. Firstly, a positive relation exists between organisational capital and firm performance. In a sample of US manufacturing and service firms, Bharadwaj et al. (1999) found that improvements in organisational capital, as measured by investments in information technology, to be positively related to firm performance, using Tobin's *q* as measurement. In addition, Bontis et al. (2000) studied firms in the Malaysian market by surveying part-time MBA students working at a variety of different companies. They also found a positive relationship between intellectual capital (organisational capital in particular) and firm performance, as indicated by the assessment of objective financial and performance related measures. Secondly, organisational capital can facilitate increased performance by augmenting the effects of human capital. In the same research, Bontis et al. (2000) also found that investment in organisational capital can increase the effectiveness of human capital. Next to this, Schiuma and Lerro (2008) compiled research and findings from a conference on the dynamics of intellectual capital. They found that organisational capital is a significant factor in transforming the intrinsic knowledge of individuals and firms into value for the company. For instance, this could occur as a result of companies having access to superior technology compared to their competitors, providing a better platform for their employees to work with and develop new items.

2.6.3 Social Capital

Lastly, Adler and Kwon (2002) compiled research on the role of social capital as defined in Section 2.5.3, and found that it is a powerful actor in firm success. Lins et al. (2017) studied the role of social capital on firm performance for large publicly traded companies in the Great Recession, and found that firms with higher social capital performed significantly better than firms with low social capital. They measured social capital by considering corporate social responsibility (hereafter: CSR) intensity and found that firms with high CSR had stock returns of up to seven percentage points higher than firms with lower CSR levels. CSR intensity is used as a metric for social capital as it consists of aspects concerning civic behaviour, reputation, consciousness, and relations between firms and their stakeholders. As such, it strongly resembles the theoretical foundations of social capital. Additionally, Stam et al. (2013) considered social capital in the form of the strength of personal networks by compiling the results of several different studies. They found that social capital had a significant positive effect on the performance of small firms.

Furthermore, Gabbay and Zuckerman (1998) researched the performance and effectiveness of corporate R&D teams in major American corporations. Social capital was measured by survey answers ranking the level of interaction within the teams and social networks on a scale. They found that social capital is a catalyst for improving interunit resource exchange and product innovation, making teams more effective and leading to increased firm performance. In addition, Rosenthal (1996) also investigated the effect of social capital (measured by interaction and networks) on the performance of teams within the manufacturing industry. Again, it was found that higher social capital led to increased team performance. These results were corroborated by Adler and Kwon (2002), who find that social capital can facilitate increased human- and organisational capital through acting as an intermediary to connect the different actors.

3. HYPOTHESIS DEVELOPMENT

By consulting the theoretical background on intellectual capital, several key effects stood out. Firstly, research has pointed out that there is a positive relationship between intellectual capital and firm performance, such that an increase in intellectual capital levels corresponds to improved business performance (e.g. Barney, 1991; Bontis, 1998; Clarke et al., 2011). This effect stems mainly from firms with higher intellectual capital being more adept at using the resources at their disposal in addition to a technological advantage leading to increased innovation. For the purposes of these hypotheses, unless specified otherwise, firm performance will be measured by considering firm efficiency (RoA) and firm profitability (RoE). The positive relationship between intellectual capital and firm performance also held true in studies conducted of US markets, however, most of these studies are concentrated during the 1990s. Yet, as with other markets, it is expected that the same result will still hold for the time period of the current study, leading to the formulation of the following hypothesis:

Hypothesis 1: *there is a positive relation between intellectual capital and firm performance.*

Secondly, in addition to research linking intellectual capital to current firm performance, studies have demonstrated that higher levels of intellectual capital are indicative of higher future firm performance (e.g. Benhabib and Spiegel, 1994; Tan et al., 2007). This is the case due to firms having access to more advanced technologies thereby stimulating innovation. Additionally, higher levels of intellectual capital increase a firm's absorptive capacity, which entails that a firm can adapt itself to new technologies and innovations more readily than others. As a result, it is expected that the presence of intellectual capital may have the property of indicating future firm value as well. This effect is amplified by the use of q as a measure of intellectual capital, as a value of higher than one is an indication that the item is a valuable investment opportunity. Hence, the presence of intellectual capital, or a q that is higher than one, should lead to higher firm performance in the long-term future. This proposition lends itself to the following hypothesis:

Hypothesis 2: *higher levels of intellectual capital are indicative of higher future firm performance.*

Thirdly, the literature review has also pointed out that intellectual capital can stimulate the growth rate of a firm by amplifying its innovative capabilities (e.g. Gabbay and Zuckerman, 1998; Kusunoki et al., 1998) and augmenting its ability to adopt superior technology (e.g. Allen, 2012; Benhabib and Spiegel, 1994). As such, it is expected that firms with higher intellectual capital will exhibit greater firm growth, as these firms innovate more and are better capable at transitioning to better technology. This firm growth is expected to be most prevalent in the growth of a firm's revenue. Therefore, this leads to the following hypothesis:

Hypothesis 3: *firms with higher levels of intellectual capital exhibit greater revenue growth.*

Fourthly, the theory also discussed some particular effects stemming from particular components of intellectual capital. Specifically, if the intellectual capital can be protected from misappropriation by other firms, the competitive advantage that it gives is exacerbated (Crook et al., 2011). Hence, it is expected that organisational capital equates to the greatest effect on firm performance. This is because organisational capital can be protected more readily than other forms of intellectual capital due to a large component of it consisting of intellectual property, which is protected by legislature. Since intellectual capital provides greater benefits to a firm if it can be protected and remain firm-specific, it is expected that it will have the greatest effect on firm performance, leading to the following hypothesis:

Hypothesis 4: *organisational capital has a relatively greater effect on firm performance than other types of intellectual capital.*

4. EMPIRICAL DESIGN

4.1 Specifications of the Dataset

The current dataset is longitudinal data composed of annual data on firms in the S&P 500 in a time period ranging from 2000 to 2015. It is an unbalanced sample, indicating that not all units are observed in all time periods. This is due to datasets missing values in certain years, and due to some firms entering at a later stage within the timeframe of the research, resulting in the exclusion of these observations. In total, the variables in the dataset feature between 3364 – 6057 observations. Furthermore, some unbalance also arises from the specification of the S&P 500. For the purposes of this research, the dataset features the most recent iteration of the S&P 500 (as of May 2022), meaning that some firms that were part of the S&P 500 in the past are not a part of the study. Moreover, some incumbent firms may have entered the S&P 500 within the current period of interest.

Several sources were consulted to produce the final dataset. The bulk of the data consists of financial firm-level data, which was gathered from Compustat North America's annual fundamental financial information. This source provides annual data on companies taken from their income statements, balance sheets, statements of cash flow, and ratio data. Furthermore, this was supplemented with data from other sources to devise specific variables. Firstly, a comprehensive dataset on patent assignments in North America was acquired from the United States Patent and Trademark Office. This dataset contained bulk, unsorted data. Consequently, using a python script, the patents were matched to the years they were granted in and matched to the companies to who the patents were assigned. Secondly, information on CSR factors was gathered from the MSCI ESG Stats database, which keeps records of individual firm performance on a variety of CSR metrics. Finally, both the aforementioned datasets were merged with the fundamental data from Compustat by identifying the firms and years to produce a final dataset.

4.2 Variables

4.2.1 Dependent Variables

The current research aims to measure firm performance and revenue growth. Clarke et al. (2011) studied prior research to find firm performance metrics which will be utilised in the current study as well. These three variables are defined as the following:

1. Return on Equity $(RoE) = \frac{Net\ Income}{Shareholders'Equity}$
2. Return on Assets $(RoA) = \frac{Net\ Income}{Total\ Assets}$
3. Revenue Growth $(RG) = \left(\frac{Current\ Revenue - Revenue\ Last\ Year}{Revenue\ Last\ Year}\right)$

In analysing the performance variables, it was found that they contained some substantial outliers. In order to deal with these, the variables were winsorised at cut-offs of 1% and 99%, limiting the effect of the spurious outliers whilst maintaining the observations. The variables are the following:

RoE Return on equity is a measure of firm performance that effectively calculates the net return on assets as it look at shareholders' equity, which refers to total assets minus liabilities. It is used to calculate profitability of a firm and allows for the comparison of performance across firms, where a higher RoE implies that the firm is performing better. RoE averages may differ across industries however, necessitating the distinction to be made between different industries.

RoA The return on assets is another performance metric which gauges the operational efficiency of a firm. Petersen and Schoeman (2008) state that it provides information about how much profits are generated by each unit of assets in a firm, thereby indicating its efficiency. The higher the RoA is, the more efficient a firm is.

RG Finally, revenue growth simply refers to the change in revenue between a year and the year prior. In doing so, it gives an accurate picture of firm size and performance between different years. As a result, it is a more effective method for analysing changes in firm performance rather than measuring firm performance outright.

4.2.2 Independent Variables

In this research, the independent variables are centred around quantifying intellectual capital. As such, there is a general measure for intellectual capital along with specific indicators for its components. The specific indicators were devised by consulting Hunter et al. (2005), who reviewed a vast plethora of research and produced a series of indicators used by the seminal papers in the field.

Q In the current study, the primary method to quantify intellectual capital is through the use of Tobin's *q*. The concept will be outlined further in Section 4.3. For the purposes of this study, a value of 1 indicates that the company is valued exactly equal to its tangible assets, whereas an overvaluation (meaning above 1) indicates the presence of intellectual capital.

4.2.2.1 Human Capital Indicators

PROD This variables indicates a firm's profits per employee. It is used in the literature to give an indication of human capital as it presents an employees' relative contribution to a firm's performance. In the current research, it is calculated by dividing net income by the total number of employees.

4.2.2.2 Organisational Capital Indicators

XRD The current variable is a measure of research and development (hereafter: R&D) expenses as reported on a company's balance sheet. As a result, it does not reflect the value of the actual outcomes of the R&D, but merely indicates that value that companies have invested in improving their organisational capital. Yet, it remains an appropriate tool to aid in quantifying total organisational capital.

PATENT This variable is a measure of the total number of patents granted to each firm per fiscal year. It is one of the primary indicators of organisational capital as it captures internally-generated intellectual property items, which are a vital part of organisational capital.

4.2.2.3 Social Capital Indicators

CSR The first indicator for social capital is an index giving firms a score based on CSR factors as in Lins et al. (2017). It was compiled by gathering data on the CSR ratings of large public companies as reported in the MSCI ESG Stats Database. In this database, records are kept of a firm's strengths and concerns across various CSR metrics, constructing a count of both. These metrics include environmental, community relations, employee relations, diversity relations, product image, and corporate governance concerns, which can be used as a tool to measure social capital (Lins et al., 2017; Stam et al., 2013). For the purposes of this study, both are valuable, leading to the construction of a net measure adding strengths whilst subtracting concerns. The maximum number of strengths and concerns varies quite a bit over the years, necessitating a scaling of the two. This is performed by dividing the strengths and concerns by the maximum value per year, leading to a yearly score per firm ranging from -1 to +1.

GDWL The second indicator to measure social capital is goodwill, as reported on a firm's balance sheet. As discussed in Section 2.5.3, the balance sheet item refers to the surplus paid for acquiring a company compared to its balance sheet valuation. As a result, this variable only accounts for externally-generated goodwill and therefore does not capture internally-generated social capital. Though it cannot be used to determine internally-generated intangibles, it is a component of overall social capital and therefore critical in its analysis.

4.2.3 Control Variables

AGE The older a company is, the more established its organisational capital qualities may be. On the other hand, a younger company may have surged forwards through their advantage in intellectual capital. In other words, a company's age may have an effect on the prevalence of intellectual capital, necessitating this control variable. In the case of two companies merging into one, the founding date of the oldest parent firm is taken as the reference point for constructing this variable.

REC Within the current research, the years 2008 – 2009 were marked by the Great Recession – one of the worst economic downturns in history and a time marred by unusual economic behaviour. As a result, the results may differ in those years, necessitating the construction of a dummy variable to indicate whether observations occur in those years or not.

SIZE A firm's size may have an impact on the prevalence of intellectual capital and what type is the most dominant. As a result, this is controlled for by including total revenue as a control variable.

LEVG The proportion of debt that a firm carries with it may have an effect on investors' behaviour, thereby potentially influencing q. If firms are overly reliant on debt, this could dissuade investors by harming the returns of the firm. As a result, it is controlled for by *levg*, which measures the leverage of the firm defines as the ratio between total assets and total debt.

gics As indicated in the theoretical background, a substantial discrepancy can occur between the relevance of intellectual capital across different industries. To be able to distinguish the effect that intellectual capital has on different types of industries, this control variable specifies which sector a firm is a part of. Specifically, the firms are categorised using the Global Industry Classification Standard (hereafter: GICS), which is used by the S&P 500 to assign companies to their respective sectors.

4.3 Economic Framework

In this research, intellectual capital is measured according to Tobin's q. In its original form, it was devised as the ratio between the market value of a firm and the replacement cost of its assets. The replacement cost refers to the value of a firm replacing all its assets for new items, thereby negating virtually all intangibles. Usually, this is measured by using the book value of equity of a firm. The current research uses the following formulation of q:

$$q = \frac{market\ capitalisation}{book\ value\ of\ equity}$$

As can be seen above, the approximation of q can be performed with a simple formula which only features items from a firm's balance sheet. Since the book value of equity takes physical assets into account, if q > 1, the company features intellectual capital. In this case, the firm is technically overvalued, making it worth more than the cost to replace its assets. Hence, the overvaluation is attributable to intellectual capital. Additionally, Levy and Duffey (2007) state that if q > 1, the relative amounts of intellectual capital can be compared across different firms and industries.

4.4 Econometric Specification

In the current research, two model specifications will be exploited. Owing to the nature of the longitudinal data, which adds a time-dimension, ordinary least squares models cannot be utilised. Instead, a generalised method of moments (hereafter: GMM) model will be exploited to test the hypotheses. All the models in the research share a baseline econometric specification, which is given by the following:

$$performance_{it} = \beta_0 + \beta_1 q_{it} + \beta hc_{it} + \beta oc_{it} + \beta sc_{it} + \beta controls_{it} + \alpha_i + \varepsilon_{it}$$

In the formula above, all items are indexed by firm (i) and year (t). The dependent variable, *performance*, stands for one of the three firm performance measures outlined in Section 4.2. Next, the main independent variable is denoted by q and represents the value for Tobin's q. Additionally, the other independent variables are indicated by *hc*, *oc*, and *sc* representing the variables for human capital, organisational capital, and social capital, respectively. Moreover, *controls* denotes the control variables included in the model. Finally, the error term is composed of two elements: α, indicating the unobserved heterogeneity (or time-invariant components), and ε referring to the idiosyncratic (or time-variant) components.

4.4.1 GMM Model

As indicated previously, the GMM model is the model of choice for conducting the current research. First introduced by Hansen (1982), it is a generic method for dynamically estimating parameters in longitudinal data models. It features an important property, namely that it controls for endogeneity. According to Wooldridge (2013), endogeneity occurs when an explanatory variable is not exogenously defined and is correlated to the error term. In essence, this means that the variable is influenced by other observations in the dataset. Since endogeneity is likely to be a problem in the current dataset, a GMM model provides an advantage over other models, as most longitudinal data models are limited by a strict exogeneity assumption. In fact, it is a dynamic model, meaning that observations may be influenced by past observations and it can be used in the presence of heteroskedasticity and autocorrelation.

The GMM model that is used in this research is a two-step system GMM model. It was developed by Arellano and Bover (1995) to use more moment conditions than the original GMM model. Fumio (2000) identifies that moment conditions are functions of the data where the expected value is zero at the true values of the parameters in the model. Estimation results are then produced by the minimisation of sample averages of the moments. As such, the use of more moments provides more reliable estimates and improves the efficiency in correcting endogeneity. Estimation is performed by building a system of two equations, namely the original equation and an equation transformed by orthogonal deviations. The first equation is given by the following equation, which is based on the baseline econometric specification:

$$DV_{it} = \beta_0 + \beta_1 DV_{it-1} + \beta_2 q_{it} + \beta hc_{it} + \beta oc_{it} + \beta sc_{it} + \beta controls_{it} + \alpha_i + \varepsilon_{it}$$

The equation above bears a strong resemblance to the original baseline equation, with one significant difference. A lag of the dependent variable is included as an independent variable in the model, reducing endogeneity concerns resulting from the dependent variable. The second equation is transformed by orthogonal deviations. According to Roodman (2009), this is a transformation that subtracts the average of all future available observations from a variable. Hence, it has an advantage over other transformation methods such as first-differencing, as these can magnify gaps in unbalanced datasets (like the current dataset) by increasing missing data. The transformation of the variables is performed by the following equation:

$$x_{it}^{\perp} = \left(\sqrt{\frac{T_{it}}{(T_{it}+1)}}\right) \times \left(x_{it} - \frac{1}{T_{it}} \sum_{s>t} x_{it}\right)$$

In the equation above, x refers to any variable and T to the number of available future observations. As such, it is computed for all observations in the dataset except for the last observation for each group, thereby minimising the loss of data. Roodman (2009) also states that an added benefit of the transformation is that the observations remain identically distributed, meaning that autocorrelation is not introduced to the model. The transformation is applied to the variables in the original equation to complete the system of two equations. This allows for the estimation of parameters for which the GMM model uses internal and external instruments. In this case, a two-step model is used, meaning that residuals from the first estimation are used to compute the final results.

To ensure that the GMM model is specified correctly, Adeleye (2018) identifies two diagnostics which will be reported in the model outputs. Firstly, the Arrellano-Bond test gauges the null hypothesis stating that the transformed error term is first and second order autocorrelated. This test statistic is reported as AR(2) in the output, and failure to reject the null hypothesis implies a correct specification of the moment conditions (i.e. AR(2) > 0.05). Secondly, the Hansen test verifies the null hypothesis of the general validity of instruments. Again, failing to reject this null hypothesis gives support to the choice of instruments in the model. These test statistics will be provided and their conditions upheld for all models in this research to ensure the validity of the results.

4.5 Data Transformation

In working with the dataset described previously, some transformations were essential to deal with skewness of some variables. If variables are highly skewed, the dataset does not take the form of a normal distribution leading to potentially spurious regression results. Most of the variables featured a high skewness score (i.e. above |0.5|), resulting in the necessity to take logarithms of these variables if they are continuous. However, many of the observations feature negative numbers, meaning that the logarithm cannot be taken of these observations. To ensure that these observations were not lost, the following log transformation was applied to the relevant variables:

$$\log(x) = sign(x) \times \log(|x| + 1)$$

In the equation above, the logarithm of each variable can be taken due to using the absolute value of each observation and hence there being no negative logarithms. By adding 1 to each observation, it is ensured that there will not be any negative outcomes of taking logarithms, considering that these only occur between 0 and 1. Finally, by multiplying the logarithm by the sign of the observation, the result will be negative only for those observations that feature an initial negative number. Moreover, by applying this transformation, it is ensured that values that were initially zero can also be featured in the research. These will now be equivalent to taking the logarithm of one, which equals zero, and can be used in the models instead of appearing as missing data after taking normal logarithms. The previous transformations result in the dataset as described in the following section.

4.6 Descriptive Statistics

To aid further understanding of the dimensions of the dataset, the following table contains the descriptive statistics for the different variables in the dataset. This includes the number of observations, mean, standard deviation, minimum, and maximum values for each variable in the dataset.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
RoE	5134	.161	.108	-.016	.351
RoA	5134	.069	.045	.003	.145
RG	4692	.08	.105	-.076	.271
logQ	5126	-.005	.097	-1.209	1.463
logPROD	4637	3.404	1.089	.012	7.725
logXRD	3346	4.593	2.534	0	9.686
logPATENT	6057	2.247	2.279	0	11.051
CSR	5137	-.035	.244	-.889	.938
logGDWL	4643	6.244	2.689	0	11.564
AGE	6057	61.625	45.567	0	230
REC	6057	.119	.324	0	1
logSIZE	5134	8.78	1.481	0	13.089
logLEVG	4305	1.713	1.227	-1.302	13.255
gics	6057	5.462	2.652	1	11

The descriptive statistics illustrate the dimensions of the variables in the dataset as described in Section 4.4. As mentioned before, some variables exhibited high values for skewness (substantially above |0.5|), necessitating logarithmic transformations. The variables that have been logarithmically transformed are denoted by the addition of *log* to their names. As Table 1 demonstrates, the total number of observations for the variables vary between 3364 – 6057. Furthermore, all variables are continuous, with two exceptions. Firstly, as mentioned before, *REC* is a dummy variable that has a value of 1 if the observation took place during the Great Recession. Secondly, *gics* is a categorical variable in the form of an integer between 1 and 11. The industry classifications that the integers correspond to are listed in Table 7 in the appendix.

A noteworthy element of the summary statistics is that the main independent variable of interest, Q, displays a mean value of -0.005, such that it is very close to 0. Since this variable has been subject to a logarithmic transformation, this means that the mean of the original variable is close to 1. This is consistent with expectations, as q converges to a value of 1 over-time.

4.7 Correlation Matrix

In Table 2, the pairwise correlation matrix for all variables is presented. To determine whether the current variables are suitable for use in the research, high collinearity between them must be avoided. If not, the model is susceptible to multicollinearity issues which may lead to spurious results. In the table, the correlation values range from 0 to |1|. Values closer to 0 are not correlated with each other, whereas values closer to |1| are highly correlated.

Table 2 indicates that the variables mostly feature low correlation values between each other. However, there are some exceptions. Firstly, the correlation value between *RoE* and *RoA* is 0.693, meaning that they are highly correlated. However, this is not an issue as these variables are never used simultaneously in the research. Secondly, there are some relatively high correlation coefficients for the organisational and social capital indicators. To test whether this presents a multicollinearity problem in the research, the variance inflation factor (hereafter: VIF) values were gauged. Generally, it is accepted that a VIF below 5 poses no problems, between 5 – 10 one should be wary of potential effects, and above 10 there will almost certainly be multicollinearity issues. The VIF testing indicated that the initial iteration of the dataset contained a variable with a VIF above 10 (see Table 8 in the Appendix for an overview). As a result, the current dataset had to be altered by removing this variable. As a result, for all remaining variables the VIF remained substantially below 5, implying that the variables do not introduce multicollinearity to the research.

Table 2: Correlation Matrix

Variables	Obs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) RoE	5134	1.000												
(2) RoA	5134	0.693	1.000											
(3) RG	4692	0.060	0.159	1.000										
(4) logQ	5126	0.013	0.008	0.021	1.000									
(5) logPROD	4637	0.221	0.312	0.063	0.013	1.000								
(6) logXRD	3346	0.034	-0.015	-0.077	-0.015	0.494	1.000							
(7) logPATENT	6057	0.054	0.060	-0.017	-0.020	0.107	0.596	1.000						
(8) CSR	5137	0.094	0.094	-0.122	-0.015	0.137	0.366	0.231	1.000					
(9) logGDWL	4643	0.062	-0.045	-0.144	0.008	-0.011	0.364	0.195	0.217	1.000				
(10) AGE	6057	0.108	-0.007	-0.216	-0.002	0.021	0.175	0.049	0.121	0.231	1.000			
(11) REC	6057	-0.040	-0.037	-0.151	0.047	-0.003	0.002	0.002	-0.146	-0.014	0.000	1.000		
(12) logSIZE	5134	0.181	0.016	-0.188	0.005	0.077	0.258	0.225	0.197	0.437	0.320	-0.012	1.000	
(13) logLEVG	4305	0.072	0.267	0.139	-0.026	0.033	0.062	0.098	0.030	-0.099	-0.101	0.016	-0.062	1.000

5. RESULTS

In the following section, the regression results of the different models will be discussed. The hypotheses will be tested in turn, using the GMM model as outlined in Section 4. This will be followed by a discussion of the implications of the results.

5.1 Hypothesis 1

In Table 3, the results for testing Hypothesis 1 are presented. This hypothesis stipulates that there is a positive relation between intellectual capital and firm performance. In total, two different specifications were created to model the hypothesis, both exploiting a GMM model design. Model 1 uses RoE as dependent variable, whereas Model 2 uses RoA as dependent variable.

Firstly, the control variables feature varying levels of significance. In Model 1, firm size is a statistically significant determinant of firm performance, with performance increasing along with firm size. Moreover, in this model, the age of a firm is also a statistically significant determinant of firm performance, though this result is not significant in Model 2. Additionally, in Model 2, leverage also has a positive impact on firm performance, however this result is not significant in Model 1. As expected, in both models firm performance is negatively affected if the observations are in the same time period as the Great Recession. Lastly, the industry classification dummies are mostly significant, with some displaying a negative relation with firm performance and some a positive relationship. It should be noted that, in this model and the next models, several of these have been automatically omitted from the model due to multicollinearity prevention.

Next, the validity of Hypothesis 1 can be analysed by considering the independent variables for intellectual capital and its components. As a result of the design of the GMM model, both include a lagged version of the dependent variable. In both cases, the lagged variable has a statistically significant (at the 1% level) positive relationship with firm performance. Furthermore, holding all else equal, q has a statistically significant positive effect (at the 1% level in both models) on firm performance by either measure. This suggests that the presence of intellectual capital stimulates firm performance and is

Table 3: GMM for the relationship between intellectual capital and firm performance

VARIABLES	(1) RoE	(2) RoA
RoE_{it-1}	0.314***	
	(0.0102)	
RoA_{it-1}		0.186***
		(0.00921)
logQ	0.0125***	0.00715***
	(0.00439)	(0.00154)
logPROD	0.0462***	0.0267***
	(0.00162)	(0.000581)
logXRD	-0.00404***	-0.00427***
	(0.000957)	(0.000621)
logPATENT	-0.00140**	0.000373*
	(0.000606)	(0.000203)
CSR	0.000260	0.00797***
	(0.00379)	(0.00206)
logGDWL	-0.00375***	-0.00207***
	(0.000912)	(0.000393)
AGE	0.000113**	2.47e-05
	(4.76e-05)	(2.76e-05)
REC	-0.0102***	-0.00102**
	(0.00123)	(0.000456)
logSIZE	0.00863***	0.000196
	(0.00196)	(0.00104)
logLEVG	-0.000736	0.00433***
	(0.00153)	(0.000436)
2.gics	0.0940***	0.0124
	(0.0154)	(0.00875)
3.gics	0.103***	0.0271***
	(0.0148)	(0.00872)
4.gics	0.118***	0.0365***
	(0.0158)	(0.00909)
5.gics	0.0879***	0.0298***
	(0.0174)	(0.00901)
6.gics	0.0719***	0.0204**
	(0.0146)	(0.00866)
7.gics	-0.0725	0.0158
	(0.0718)	(0.0729)
8.gics	0.0744***	0.0229**
	(0.0147)	(0.00893)
9.gics	0.0152	0.00730
	(0.0170)	(0.00936)
11.gics	0.0162	-0.0149*
	(0.0155)	(0.00872)
Constant	-0.146***	-0.0255*
	(0.0226)	(0.0136)
Observations	2,477	2,477
Number of groups	237	237
AR(2) value	0.419	0.513
Hansen value	0.082	0.105

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

therefore concurrent with Hypothesis 1. Moreover, a closer look at some of the component-specific indicators corroborates this result. In both models, employee productivity has a statistically significant positive effect on firm performance, suggesting that higher levels of human capital lead to increased firm performance, provided that other factors are held constant. In addition, Model 2 indicates that both patent generation and the CSR metric have a statistically significant positive relationship with firm performance. These results imply that, ceteris paribus, social and organisational capital have a positive effect on firm performance.

In contrast, the variables that denote organisational capital mostly suggest statistically significant negative relations between itself and firm performance in both models. All other things being equal, research and development costs have a statistically significant (at the 1% level) adverse effect on firm performance. The same holds for patent generation in Model 1. Similarly, in both models, goodwill has a statistically significant (at the 1% level) negative relationship with firm performance, suggesting that social capital is negatively related to firm performance. As a result, the outcomes for these variables do not support that intellectual capital has a positive effect on firm performance, and thus do not lend their support to Hypothesis 1. There are various factors which could explain these results. Firstly, *XRD* measures the amount that a firm invests into R&D in a given year. As an increase in R&D investment may not lead to innovations coming into fruition in that same year, the investment may pay off in the long-run, but decrease performance in the short-run. Secondly, a firm may be pressured to innovate by its competition, which is outperforming them with novel ideas and innovations. Hence, to ensure they remain competitive, the firm is forced to invest more into R&D, with its effects following in the years that follow. The same holds for patent generation, with it being likely that its effects are only realised when the company brings the patents to the market, which follows some years behind their generation.

The case of *GDWL*, which measures the value of externally-generated intellectual capital, is somewhat different to that of the organisational capital indicators. Although the same principle applies that the positive effects of the purchased assets may have a time lag and improve performance later, another effect may also be at play. As mentioned in Section 4, *GDWL* measures only intangible assets purchased from another entity. If this is the case, a firm that purchases more (meaning *GDWL* is higher) may be bridging a gap in their total stock of intellectual capital and may have less than firms who do not have a high value for *GDWL*. As a result, a negative coefficient could actually indicate that the firm has a higher stock of intellectual capital, making purchasing more assets redundant. It is inconclusive which of these effects prevail and thus, due to the ambiguous nature of this variable, it cannot be stated with certainty whether it supports Hypothesis 1.

5.2 Hypothesis 2

In Table 4 the results for testing Hypothesis 2 are presented. This hypothesis postulates that higher levels of current intellectual capital are indicative of higher future firm performance. Two different model specifications were utilised: one using RoE as dependent variable and the other using RoA. In Hypothesis 2, the relationship between future firm performance and intellectual capital is analysed. To allow this, the firm performance variables (RoE and RoA) of two or five years in the future were coupled with the other variables that lag two or five years behind the performance variables. So, in essence, the variables from observations at time *t* were coupled to firm performance variables at either *t+2* or *t+5*. In doing so, future firm performance is modelled. Models 1 and 2 consider firm performance two years in the future, whilst Models 3 and 4 consider firm performance of five years in the future. Similar to Hypothesis 1, RoE and RoA are used as performance variables and modelled using a GMM model.

5.2.1 Models 1 and 2

As mentioned before, these models consider firm performance of two years in the future. The results indicate that some variables lose their significance. For the controls, both models indicate that observations taking place in the Great Recession have a statistically significant positive relationship with future firm performance. This is expected, as a temporary economic downturn makes it more likely that future performance is better. Furthermore, Model 2 indicates that age is negatively correlated with performance. Additionally, Model 1 shows a positive relationship between firm size and performance, and a negative relationship between firm leverage and performance. Conversely, Model 2 shows the opposite: a negative relationship between firm size and performance, versus a positive correlation between leverage and firm performance. All previous results are

Table 4: GMM results for the effect of intellectual capital on future firm performance

VARIABLES	(1) RoE (2 years)	(2) RoA (2 years)	(3) RoE (5 years)	(4) RoA (5 years)
FUTURE2RoE $_{it-1}$	0.816***			
	(0.0837)			
FUTURE2RoA $_{it-1}$		0.0844***		
		(0.0129)		
FUTURE5RoE $_{it-1}$			0.781***	
			(0.0811)	
FUTURE5RoA $_{it-1}$				0.0633***
				(0.0105)
logQ	-0.0284	-0.0254***	0.00115	-0.00931*
	(0.0211)	(0.00586)	(0.0133)	(0.00515)
logPROD	-0.00269	0.00586***	-0.0120	0.00343***
	(0.00293)	(0.000936)	(0.00380)	(0.00126)
logXRD	0.0123***	0.00326**	0.0169***	0.00248*
	(0.00264)	(0.00131)	(0.00265)	(0.00128)
logPATENT	-0.00708***	0.00103	-0.0101***	-0.000711
	(0.00212)	(0.000769)	(0.00207)	(0.000912)
CSR	0.0358***	0.0210***	0.00840	0.0274***
	(0.0112)	(0.00484)	(0.0144)	(0.00603)
logGDWL	-0.000740	0.00304**	-0.00592**	0.00136
	(0.00242)	(0.00119)	(0.00239)	(0.00113)
AGE	3.87e-05	-8.47e-05*	2.02e-05	-8.78e-05*
	(0.000115)	(4.35e-05)	(0.000100)	(4.57e-05)
REC	0.0150***	0.00851***	0.00245	0.00209
	(0.00318)	(0.00137)	(0.00271)	(0.00134)
logSIZE	0.00955***	-0.00670***	0.0118***	-0.00482***
	(0.00357)	(0.00155)	(0.00383)	(0.00144)
logLEVG	-0.00566**	0.00341***	-0.00413	0.00303***
	(0.00284)	(0.00104)	(0.00267)	(0.00111)
2.gics	-0.0623	-0.0993***	0.0673*	-0.0700***
	(0.0484)	(0.0239)	(0.0349)	(0.0186)
3.gics	-0.0607	-0.0907***	0.0655*	-0.0549***
	(0.0476)	(0.0243)	(0.0376)	(0.0195)
4.gics	-0.0292	-0.0649***	0.0549	-0.0426**
	(0.0475)	(0.0232)	(0.0352)	(0.0170)
5.gics	-0.0218	-0.0786***	0.0876**	-0.0454**
	(0.0469)	(0.0232)	(0.0395)	(0.0184)
6.gics	-0.106**	-0.0810***	0.00165	-0.0562***
	(0.0434)	(0.0230)	(0.0329)	(0.0178)
8.gics	-0.0958**	-0.0705***	0.0320	-0.0364**
	(0.0454)	(0.0220)	(0.0334)	(0.0174)
9.gics	-0.105	-0.209**	0.151	-0.149*
	(0.165)	(0.0884)	(0.178)	(0.0856)
11.gics	-0.385**	-0.194***	-0.0938	-0.100**
	(0.178)	(0.0647)	(0.0997)	(0.0425)
Constant	0.0855	0.183***	0.00696	0.160***
	(0.0628)	(0.0298)	(0.0530)	(0.0228)
Observations	863	863	863	863
Number of groups	111	111	111	111
AR(2) value	0.208	0.060	0.187	0.060
Hansen value	0.432	0.337	0.245	0.159

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

statistically significant at the 1% level. Lastly, Model 2 features only significant industry dummies, whereas they mostly lose their significance in Model 1.

As expected, the dependent variable lags for both performance metrics is positively related to future firm performance at the 1% level. However, the independent variables vary in their significance across the models. Firstly, Model 2 indicates that Q has a negative statistically significant relation with future firm performance. This indicates that future firm performance is negatively impacted by the present-day prevalence of intellectual capital. Thus, it does not provide support for Hypothesis 2. Moreover, Model 1 indicates that patent generation has a negative relationship with firm performance, further detracting from the support for Hypothesis 2.

In contrast, both models indicate that CSR performance has a statistically significant relationship (at the 1% level) with firm performance, and Model 2 indicates that this is the same for goodwill, albeit at the 5% level of significance. This implies that, holding all else equal, social capital has a positive effect on firm performance of two years in the future. Furthermore, Model 2 shows that employee productivity is statistically significantly (at the 1% level) positively correlated to future firm performance. Again, provided all else is held constant, this suggests that human capital has a positive effect on future firm performance. Crucially, both models indicate that *XRD* has a statistically significant positive relationship with future firm performance as well. This result is noteworthy as Hypothesis 1 indicated that R&D expense has a negative relationship with current firm performance, but it was speculated that these effects may come into fruition at a later stage. The results for Models 1 and 2 indicate that, ceteris paribus, this is indeed the case as R&D expense does improve firm performance two years in the future.

Overall, these models feature results that do not wholly coincide with expectations and lend limited support to the hypothesis. An important remark here is that predicting the future is notoriously difficult to do in economics. This is because it becomes harder to attribute changes in outcomes solely to the variables in the model. The result for q as having a negative relation to future firm performance is contrary to expectations, but could be explained by the nature of Tobin's q as an investment metric. Though it gives an indication of the presence of intellectual capital, an overvaluation (i.e. $q > 1$) may lead to lower future firm performance due to the firm's stock cooling down. As q converges to 1 over-time, it could be the case that a lower q leads to higher future firm value as the firm must experience increased performance to reach a q of around 1.

5.2.2 Models 3 and 4

These models consider firm performance of five years in the future. Akin to the previous case, Model 4 indicates that firm age and size have a negative relationship with future firm performance, whereas leverage has a positive relationship with it. On the other hand, Model 1 suggests a positive relationship between firm size and future performance.

As in the previous models, the dependent variable lags are statistically significantly (at the 1% level) related to positive future firm performance. Again, Q has a statistically significant (at the 10% level) relationship with firm performance in Model 4, featuring RoA as performance metric. As before, this does not lend its support to Hypothesis 2. In Model 3, holding other factors constant, patent generation and goodwill also have negative effects on firm performance. In contrast, Model 4 indicates that CSR performance has a statistically significant (at the 1% level) positive relationship with firm performance. Additionally, the model indicates that employee productivity also has a statistically significant positive relationship with future firm performance. The most important result is that both Models 3 and 4 again feature statistically significant positive values for the coefficients for *XRD*. This means that, holding all else equal, current investment in R&D increases a firm's performance five years in the future.

5.3 Hypothesis 3

In Table 5 the results for testing Hypothesis 3 are presented. In this hypothesis, it is theorised that firms with higher levels of intellectual capital exhibit greater revenue growth. The model uses revenue growth (*RG*) as dependent variable to measure firm performance as a growth rate between different years.

Table 5: GMM results for the effect of intellectual capital on revenue growth

VARIABLES	(1) RG
RG_{it-1}	0.187***
	(0.0127)
logQ	0.0414***
	(0.0111)
logPROD	0.00363*
	(0.00199)
logXRD	0.000390
	(0.00132)
logPATENT	0.00241***
	(0.000706)
CSR	-0.0533***
	(0.00661)
logGDWL	-0.000345
	(0.000923)
AGE	-0.000190***
	(4.91e-05)
REC	-0.0544***
	(0.00278)
logSIZE	-0.00477***
	(0.00156)
logLEVG	0.00518***
	(0.00161)
2.gics	0.000687
	(0.0168)
3.gics	0.00975
	(0.0158)
4.gics	0.0298
	(0.0182)
5.gics	0.0144
	(0.0174)
6.gics	0.0277*
	(0.0153)
7.gics	0.119
	(0.165)
8.gics	0.0209
	(0.0140)
9.gics	0.0683***
	(0.0183)
11.gics	-0.00558
	(0.0639)
Constant	0.0795***
	(0.0252)
Observations	2,276
Number of groups	227
AR(2) value	0.121
Hansen value	0.162

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Model 1, the control variables are mostly statistically significant at the 1% level. Firm age, firm size and the dummy variable indicating the Great Recession are all significant, projecting a negative relationship with firm growth. In contrast, leverage has a statistically significant positive relationship with firm growth in the model. The industry dummies are mostly statistically insignificant, with some exceptions that have a significant positive relationship with revenue growth.

More importantly, Hypothesis 3 can be gauged by considering the independent variables of interest. In the model, the lagged dependent variable has a statistically significant positive relationship with revenue growth. Furthermore, Q has a statistically significant positive effect on firm growth, implying with all other factors held constant, the presence of intellectual capital stimulates firm growth. Hence, this result supports Hypothesis 3. In addition, indicators signifying both human and organisational capital also have statistically significant positive relations with revenue growth. Ceteris paribus, increases in employee productivity and patent generation both improve firm growth, supporting Hypothesis 3. In contrast to the other components of intellectual capital, this model suggests that social capital has a negative relationship with firm growth. Whilst the result for goodwill is not significant, CSR performance has a statistically significant (at the 1% level) negative relationship with firm growth. As such, holding all else equal, increases in CSR performance negatively affect revenue growth rates. Consequently, this does not support Hypothesis 3.

The aforementioned negative effects of social capital are remarkable as this is contrary to expectations. This finding could occur due to multiple reasons. Firstly, the effects of social capital may lag behind somewhat, such that they are not imposed on firm growth immediately. Secondly, considering its nature as an intermediary for improving human and organisational capital, it could be that it actually increases firm growth through indirect effects that are not captured in this model. To gain a better understanding of this phenomenon, more research is required in this area.

5.4 *Hypothesis 4*

In Table 6 the results for testing the validity of Hypothesis 4 are presented. Hypothesis 4 proposes that organisational capital has a relatively greater effect on firm performance than other types of intellectual capital. To test this hypothesis, the variables in the dataset had to be adjusted to allow for comparisons. In previous models, the different variables were measured on vastly different scales with completely different means and standard deviations (demonstrated in the descriptive statistics). Due to these differences, the magnitudes of the coefficients cannot be used to compare the different variables. Hence, the data must be treated by the process of standardisation.

Standardisation is a process used to ensure that different variables are on the same scale, which allows comparisons between them. This is achieved by applying the following formula to the variables:

$$standardised\ variable = \frac{variable - \bar{x}}{\sigma}$$

In the formula above, the standardised variable is created by subtracting observations by the mean for that variable and dividing this by the standard deviation for the variable. As such, the variables can now be modelled by exploiting another set of RE models. Similar to the testing of Hypothesis 1, there are two different model specifications where the first uses RoE, and the latter uses RoA as dependent variable.

In testing this hypothesis, the only variables of interest are the independent variables. Specifically, the magnitudes and significance of their coefficients are crucial to the analysis. Considering the fact that the variables have been standardised, the coefficient with the greatest magnitude has the greatest effect on the dependent variable, provided that it is a statistically significant result.

In both models, the results are similar to each other. Provided all else is held equal, the lags of the dependent variables have the greatest effects on firm performance by a substantial margin. In both models the effect of the lag is statistically significantly positive

Table 6: GMM results for the magnitudes of independent variables on firm performance

VARIABLES	(1) RoE	(2) RoA
RoE_{it-1}	0.302***	
	(0.00960)	
RoA_{it-1}		0.188***
		(0.00930)
logQ	0.0163***	0.0191***
	(0.00405)	(0.00289)
logPROD	0.476***	0.626***
	(0.0173)	(0.0158)
logXRD	-0.139***	-0.209***
	(0.0242)	(0.0322)
logPATENT	-0.0110	0.0167
	(0.0124)	(0.0110)
CSR	0.00235	0.0497***
	(0.00974)	(0.0112)
logGDWL	-0.0745***	-0.124***
	(0.0216)	(0.0253)
AGE	0.0638***	0.00837
	(0.0210)	(0.0245)
REC	-0.107***	-0.0240**
	(0.0121)	(0.00937)
logSIZE	0.116***	-0.00869
	(0.0265)	(0.0339)
logLEVG	-0.0147	0.114***
	(0.0192)	(0.0127)
2.gics	0.909***	0.281
	(0.144)	(0.206)
3.gics	1.003***	0.569***
	(0.143)	(0.207)
4.gics	1.132***	0.813***
	(0.142)	(0.206)
5.gics	0.773***	0.639***
	(0.162)	(0.208)
6.gics	0.705***	0.495**
	(0.134)	(0.203)
7.gics	-1.205*	-0.527
	(0.643)	(1.561)
8.gics	0.817***	0.454**
	(0.141)	(0.214)
9.gics	0.362**	0.189
	(0.155)	(0.223)
11.gics	0.163	-0.345*
	(0.143)	(0.206)
Constant	-0.634***	-0.261
	(0.131)	(0.195)
Observations	2,477	2,477
Number of groups	237	237
AR(2) value	0.410	0.481
Hansen value	0.157	0.191

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

on the firm performance metrics. Considering the independent variables, and holding all else equal, employee productivity has the greatest effect on firm performance, by the virtue of their coefficients featuring the greatest magnitude. Moreover, the results are statistically significant at the 1% level in both models. This result contrasts expectations and Hypothesis 4, as this suggests that *PROD*, which is categorised as human capital, has the greatest effect on firm performance instead of an indicator for organisational capital. In fact, the indicators for organisational capital mostly have statistically significant negative relationships with firm performance, holding other factors constant. In both models, R&D spending negatively affects firm performance, and in Model 1 patent generation does as well. In contrast, Model 2 features a positive coefficient for patent generation. As such, these results do not support Hypothesis 4. Finally, social capital also has a negative effect on firm performance, ceteris paribus. Goodwill has a statistically significantly negative relationship with firm performance in both models. However, this effect is lessened by CSR score having a significant positive effect on firm performance in Model 2.

The previous results are surprising and do not correspond to the expectations based on the theoretical background. A common view in the literature was that if intellectual capital can be protected from misappropriation, it can lead to a sustained competitive advantage (e.g. Barney, 1991; Crook et al., 2011). Since organisational capital is firm-specific, and has a higher propensity for protection than other types of intellectual capital, it was expected that organisational capital would have the greatest effect on performance. The current research does not support this. In fact, in these models it suggests that organisational capital has a negative effect on firm performance. As before in testing Hypothesis 1, this could occur due to lags in its effects taking place, or it actually signifying a shortage in intellectual capital. Furthermore, the fact that organisational capital can be protected more readily does not necessarily imply that its effects are greater than other types of intellectual capital. This could also occur due to organisational capital being firm-specific, decreasing its value for other firms. In addition, human capital is arguably the most prominent form of intellectual capital in the literature. For example, one of the precursors of discussing intellectual capital was Marshall (1890), who specifically mentioned human capital. Research since then has predominantly featured human capital, implying that this might be the most prevalent form of intellectual capital.

5.5 Supplementary Analysis

To assess the robustness of the results, the hypothesis testing was repeated with several additional model specifications. Specifically, the testing was repeated using different forms of the GMM model and using other types of longitudinal data estimators. Furthermore, the robustness of the models was tested by using additional dependent variable lags in the GMM specification. In addition, robustness of the results for the independent variables was tested by using a composite performance measure and by running the models using only component-specific indicators for intellectual capital. Next, the models were run using year dummies as a control variable instead of industry dummies. Lastly, Hypothesis 2 was modelled using future performance values both shorter and longer in the future to give more insight into the overall effects of intellectual capital on future firm performance. All the tables that are referred to in this section are listed in the appendix of this paper.

Initially, Table 9 presents the results for running the model for Hypothesis 1 with a fixed effects (hereafter: FE) and a difference GMM specification. Although the results using an FE model are very similar to the current specification, this model cannot be used due to the endogeneity concerns in this research. Additionally, this model can be used to verify whether the system GMM model as used in this research was the correct specification of GMM models. Table 9 also reports the results for testing Hypothesis 1 with a difference GMM model. This model suffers from an issue that it can report results with a downward bias, which can be verified by contemplating the Bond rule-of-thumb. This test compares the coefficients for the lagged dependent variables across an FE and a difference GMM model. If this coefficient is equal to, or lesser than, the same coefficient in the FE model (which serves as a lower-bounds estimate), a system GMM is more appropriate to use. Table 9 indicates that the coefficient for RoE_{it-1} is lower for the difference GMM model in column 2, meaning that a system GMM model is the correct specification for the current research.

Next, the hypothesis testing was repeated using additional time lags for the dependent variable. By adding more time lags, endogeneity may be accounted for to a further extent; by controlling for additional past observations, it makes current observations less dependent on previous iterations. The results for the different hypotheses are reported in Table 10 and 11. The output shows that the results are very similar to those reported in this research; the only differences are slight changes in the magnitude of coefficients and significance levels of some of the control variables. As such, this indicates that a single time lag is sufficient to control for the endogeneity in the model, thereby validating the use of one time lag in the main results of this research.

Furthermore, the robustness of the independent variables was tested in two ways. Firstly, the model for Hypothesis 1 was replicated using a composite performance measure of RoE and RoA as the dependent variable. Table 12 reports these results and shows that the results indicate the same, apart for differing magnitudes and the loss of significance for patent generation and CSR score. Secondly, the robustness of the results for the component-specific indicators was tested by repeating the testing of all hypotheses, but removing the main independent variable *Q*. These outputs are reported in Table 13, 14, and 15. These tests all provide nearly identical results for the independent variables, except for their magnitudes. Thus, these models confirm the robustness of the results for the independent variables.

In addition, the robustness of the results was tested further by utilising year dummies as control variables. This means that this replaces the dummy variable signifying the Great Recession as, in essence, this is also a dummy representing specific years. Moreover, the *GICS* was also removed as this variable was dropped altogether due to multicollinearity. The results are reported in Table 16, 17, and 18. The outputs show that the results remain largely the same across all the models. However, Hypothesis 1 now features positive values for CSR score where they were not significant in both models in the main results. Next, Hypothesis 2 and 3 are also similar, but there is a large loss of significance of the variables across the models. Lastly, Hypothesis 4 reports the same results, but *XRD* has a much greater effect than before. As such, using year dummies does affect the significance of the models, but the significant coefficients report the same results as those in the main results tables.

Finally, the robustness of the results in Hypothesis 2 were tested by using future performance variables of different times in the future. Specifically, the shorter-term was tested by looking at performance of one year in the future, and the longer-term was gauged by considering at performance of eight years in the future. The results are reported in Table 19. Firstly, the one-year future performance suggests that, holding all else equal, employee productivity now has a negative effect and CSR score now has no effect on future firm performance. For the other variables, the results are similar in the original model specification and this specification. Secondly, the eight-year future performance variable sees a substantial loss of significance in the variables across the models. Interestingly, only Q and CSR score are now statistically significantly positive, but the low number of observations take away from the explanatory power from these models. Overall, shorter-term tests confirm similar results to the main findings whilst the longer-term tests lose explanatory power due to a lack of observations.

6. CONCLUSION

The aim of this research was to examine the effect of intellectual capital on firm performance in a sample of S&P 500 firms between the fiscal years of 2000 – 2015. The theoretical background indicated that intellectual capital rose to prominence quite recently, and that measuring it is difficult due to a lack of an undisputed methodology to quantify it. It was found that q was effective as a proxy for intellectual capital, which consists of three primary components: human, organisational, and social capital. By exploiting a two-step system GMM model, the impact and prevalence of intellectual capital on firm performance could be quantified and assessed.

As the theoretical background had already indicated, successfully measuring intellectual capital proved to be difficult. The results indicated that there was mixed support for the hypotheses. Hypothesis 1 surmised that there is a relationship between intellectual capital and firm performance. By looking at the proxy for intellectual capital, q, Hypothesis 1 was supported. However, when looking at component-specific indicators, there was only limited support for the hypothesis. Furthermore, in Hypothesis 2 it was stated that intellectual capital is indicative of higher future firm performance. The results did not fully coincide with expectations, as q pointed to negative effects on future firm performance. However, some of the component-specific indicators, most prominently R&D expense, which did not have a positive effect on current performance, did have positive effects on future firm performance. In addition, Hypothesis 3 proposed that intellectual capital stimulates growth rates. Support was found for this hypothesis, with q and some indicators being significantly positive. Only the indicators for social capital did not corroborate this result. Lastly, Hypothesis 4 stipulated that organisational capital has a greater effect on firm performance than the other components of intellectual capital. No support was found for this hypothesis; in fact, it was found that human capital has the greatest effect on firm performance.

In essence, some hypotheses were supported by the results, others were prone to inconclusive results, and others were not supported. Some of the reasons that explain the results being contrary to expectations were that these variables may feature delayed effects, specifically for R&D expense, patent generation, and goodwill. This was partially supported by testing future performance, where it was found that R&D expense and goodwill did have positive effects on future performance. For patent generation, this was not upheld, suggesting that this variable does not have a positive effect on firm performance. In addition, Q was found to be positive in all models except for the model using future performance as dependent variables. Though this would suggest that intellectual capital is negatively related to future performance, this can be explained by its nature as an investment metric. As stated by Tobin (1969), the long-run equilibrium value for Q is 1, meaning that it eventually converges to this value. As such, when gauging the effects of intellectual capital on future performance, the indicators for the components may give more accurate results due to Q being downward-biased in the long-run.

Furthermore, the current research does not support Hypothesis 4. Contrary to expectations, it was found that human capital has the greatest effect on firm performance relative to the other indicators. Moreover, this result was confirmed in the robustness testing as well. The expectation was that organisational capital has the greatest effect on firm performance due to the fact that it can be protected from misappropriation more readily than other forms of intellectual capital. Though this may be true, this does not entail that its effects are also greater than the other components per se. In fact, human capital may have the greatest effect due to several reasons. Firstly, it is the only form of intellectual capital that can function as a standalone factor; both social and organisational capital require human capital to operate, but human capital can function by itself. A firm may have significant organisational capital advantages, but it would still require effective human capital to utilise everything to its full potential. Secondly, human capital also has the added benefit of increasing absorptive capacity (Benhabib and Spiegel, 1994). That is, higher levels of human capital can lead to more rapid adoption and implementation of technologies developed elsewhere, thereby increasing firm performance. As a result, these factors may ensure that human capital does have a relatively greater effect on firm performance than other components, meaning that Hypothesis 4 is not supported.

Although the research provides interesting perspectives, the research was hampered by some limitations. Firstly, and most importantly, as the theoretical background also suggested, measuring intellectual capital stays arbitrary. Although q does seem to excel at proxying intellectual capital, it cannot be used as a precise measurement to quantify it. It becomes virtually impossible to empirically confirm that any deviation in q from 1 is attributable to intellectual capital. Moreover, even when individual components are distinguished and accounted for, it can only be measured conclusively if it can be assumed that all indicators of the components are included. Considering that there are hundreds, if not thousands, of different potential indicators for the components, this assumption cannot be fulfilled, certainly not within the scope of the current research. As a result, it cannot be said with certainty that this research provides an adequate measure of intellectual capital.

Secondly, there were some limitations in regards to the data and variable selection. The dataset suffered from quite a few missing values. From some variables more were missing than others, but overall this decreased the total number from around 6000 to around 2500 in most models. By using other data sources, or combining multiple sources into one, a more complete dataset could be derived which leads to more accurate results. Furthermore, as mentioned previously, there is a vast plethora of potential indicators for the different components of intellectual capital. Although the current research features some key, relevant indicators, increasing the count of relevant variables would paint a better picture of the performance of intellectual capital. It is not in the scope of the current research, but in a larger study adding a more exhaustive list of indicators would create a more comprehensive piece of research, improving the reliability of the results.

Despite the research having some limitations, it makes some contributions to the literature by finding support for several studies performed in the past. Firstly, previous research linking increases in intellectual capital to improved firm performance was corroborated (e.g. Barney, 1991; Bontis, 1998; Clarke et al., 2011). Secondly, this research supports the notion that intellectual amplifies a firm's innovative capabilities (e.g. Gabbay and Zuckerman, 1998; Kusunoki et al., 1998) and augmenting its absorptive capacity (e.g. Allen, 2012; Benhabib and Spiegel, 1994) by finding that it leads to higher revenue growth rates. Moreover, this paper brings some new insights to the field of intellectual capital research, particularly for its components. It was found that human capital seems to have the greatest effect on firm performance, but that different forms of intellectual capital may be negatively correlated with firm performance in specific cases. For instance, the case of increases in intellectual capital being caused by the necessity of bridging a technology gap, or others poaching superior intellectual capital.

In addition to this research making some contributions to the intellectual capital literature, it also features some implications for firms and policymakers. Firstly, this research indicates that intellectual capital does have a positive effect on firm performance, making it a viable strategy for firms to invest in it. In particular, human capital has the most substantial effect on firm performance, positively affecting it both in the future and in the present. As such, it is worthwhile for firms to invest in human capital, for instance by improving training and benefits. However, given that human capital is inherent in people, meaning it cannot be owned by organisations, firms should be wary that it can be poached away. Furthermore, policymakers could also be enticed to stimulate intellectual capital by reaping the benefit of improving economic growth. For example, investments in education or subsidies in R&D programmes could improve overall levels of intellectual capital in the economy, leading to improved economic performance.

In conclusion, the current research aimed at exploring the effects of intellectual capital on firm performance. Although the results were not completely aligned with expectations, the research points towards some interesting findings and noteworthy avenues for further research. The current research has contributed to the understanding of the dynamics of intellectual capital, but further research in this area is required to draw conclusive results about its exact effects on firm performance.

7. REFERENCES

Adeleye, B.N. (2018). Understanding Generalised Method of Moments [Lecture]. *Covenant University: Department of Economics and Development Studies*

Adler, P.S., & Kwon, S.W. (2002). Social Capital: Prospects for a New Concept. *The Academy of Management Review*, 27(1), pp. 17-40

Allen, R.C. (2012). Technology and the great divergence: global economic development since 1820. *Explorations in Economic History*, 49, pp. 1-16

Andriessen, D., & Tissen, R. (2001). *Weightless Weight – Find your Real Value in a Future of Intangible Assets*, London: Pearson Education

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), pp. 29-51

Arrow, K.J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies*, 29(3), pp. 155-173

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1), pp. 99-120

Barro, R.J. (2001). Human capital and growth. *The American Economic Review*, 91(2), pp. 12-17

Becker, G.S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Chicago: The University of Chicago Press

Beers, B. (2022). Why Do Investors Use the S&P 500 As a Benchmark?. *Investopedia*, retrieved from: https://www.investopedia.com/ask/answers/041315/what-are-pros-and-cons-using-sp-500-benchmark.asp

Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development: Evidence from aggregate cross-country and regional US data. *Journal of Monetary Economics*, 34, pp. 143-173

Bharadwaj, A.S., Bharadwaj, S.G., & Konsynski, B.R. (1999). Information technology effects on firm performance as measured by Tobin's q. *Management science*, 45(7), pp. 1008-1024

Blanchard, O., Amighini, A., & Giavazzi, F. (2010). *Macroeconomics a European Perspective*. London: Pearson Education

Bloom, M. (2009). Accounting For Goodwill. *ABACUS*, 45(3), pp. 379-389

Bo, H. (1999). The Q theory of investment: does uncertainty matter. *University of Groningen*

Bontis, N. (1998). Intellectual capital: an exploratory study that develops measures and models. *Management Decision*, 36(2), pp. 63-76

Bontis N., Keow C.C., & Richardson S. (2000). Intellectual capital and business performance in Malaysian industries. *Journal of Intellectual Capital*, 1(1), pp. 85-100

Boulding, K.E. (1966). The Economics of Knowledge and the Knowledge of Economics. *The American Economic Review*, 56(1), pp. 1-13

Brooking, A. (1996). *Intellectual Capital: Core Asset for the Third Millennium Enterprise*. New York: International Thomson Business Press

Chen, D.H.C. & Dahlman, C.J. (2006). The Knowledge Economy, the KAM Methodology and World Bank Operations. *World Bank Institute*, 37256

Chen Y.S., Lin M.J., & Chang C.H. (2006). The influence of intellectual capital on new product development performance – the manufacturing companies of Taiwan as an example. *Total Quality Management*, 17(10), pp. 1323-1339

Clarke, M., Seng, D., & Whiting, R.H. (2011). Intellectual capital and firm performance in Australia. *Journal of intellectual capital: Working Paper Series*

Coleman, J.S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*, 94, pp. S95-S120

Corrado, C.A., Hulten, C.R., & Sichel, D.E. (2006). Intangible Capital and Economic Growth. *National Bureau of Economic Research*, 11948

Crook, T.R., Todd, S.Y., Combs, J.G., Woehr, D.J., & Ketchen, D.J. (2011). Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. *Journal of Applied Psychology*, 96(3), pp. 443-456

Drucker, P. (1969). *The Age of Discontinuity; guidelines to our changing society*. New York: Harper and Row

Edvinsson, L. (1996). Developing a Model for Managing Intellectual Capital. *European Management Journal*, 14(4), pp. 356-364

Edvinsson, L., & Malone, M.S. (1997). *Intellectual Capital: Realizing Your Company's True Value by Finding its Hidden Brainpower*. New York: Harper Business.

Engelbrecht, H.J. (2003). *Data Issues in the New Economy*. San Diego: Elsevier (Academic Press)

Gabbay, S.M., & Zuckerman, E.W. (1998). Social capital and opportunity in corporate R&D: The contingent effect of contact density on mobility expectations. *Social Science Research*, 27(2), pp. 189-217

Galor, O. (2004). From Stagnation to Growth: Unified Growth Theory. *Centre for Economic Policy Research*, 4581, pp. 1-104

Goldin, C.D. (2016). Human Capital. *Harvard University*

Hall, B.H., Thoma, G., & Torrisi, S. (2007). The market value of patents and R&D: Evidence from European firms. *Academy of Management Proceedings*, 1, pp. 1-6

Hall, R. (1992). The strategic analysis of intangible resources. *Strategic Management Journal*, 13(2), pp. 135-144

Handy, C.B. (1989). *The Age of Unreason*. London: Arrow Books Ltd

Hansen, L.P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50, pp. 1029-1054

Hayashi, F. (1982). Tobin's Marginal q and Average q: A Neoclassical Interpretation. *Econometrica*, 50(1), pp. 213-224

Hayashi, F. (2011). *Econometrics*. Princeton: Princeton University Press

Hejazi, R., Ghanbari, M., & Alipour, M. (2016). Intellectual, human and structural capital effects on firm performance as measured by Tobin's Q. *Knowledge and Process Management*, 23(4), pp. 259-273

Hunter, L., Webster, E., & Wyatt, A. (2005). Measuring Intangible Capital: A Review of Current Practice. *Intellectual Property Research Institute of Australia*, 16(4)

Jacobs, J. (1969). *The Economy of Cities*. New York: Random House

Jacobs, J. (1984). *Cities and the wealth of nations*. New York: Random House

Jansen J.J.P, Tempelaar M.P., van den Bosch F.A.J., & Volberda H.W. (2009). Structural differentiation and ambidexterity: the mediating role of integration mechanisms. *Organization Science*, 20, pp. 797-811

Kaldor, N. (1966). Marginal Productivity and the Macro-Economic Theories of Distribution: Comment on Samuelson and Modigliani, *Review of Economic Studies*, 33(4), pp. 309-319.

Kusunoki K., Nonaka I., & Nagata A. (1998). Organizational capabilities in product development of Japanese firms: a conceptual framework and empirical findings. *Organization Science*, 9, pp. 699-718

Levy, F., & Duffey, M.R. (2007). A review of existing methods to quantify intangible assets, *International Journal Accounting, Auditing and Performance Evaluation*, 4(4/5), pp. 382-399

Lins, K.V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4), pp. 1785-1824

Lucas, R.E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1), pp. 3-42

Lundvall, B.A. & Johnson, B. (1994). The Learning Economy. *Journal of Industry Studies*, 1(2), pp. 23-42

Luthy, D.H. (1998). Intellectual capital and its measurement. *Proceedings of the Asian Pacific Interdisciplinary Research in Accounting Conference*, pp. 16-17

Marshall, A. (1890). *Principles of Economics*. London: MacMillan

Megna, P. & Klock, M. (1993). The Impact of Intangible Capital on Tobin's q in the Semiconductor Industry. *American Economic Review*, 83(2), pp. 265-269

Minovski, Z., & Jancevska, I. (2018). The role on intellectual capital and its accounting recognition and measurement. *The Journal of Contemporary Economic and Business Issues*, 5(1), pp. 67-76

Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. *The Academy of Management Review*, 23(2), pp. 242-266

Nelson, R. (1959). The Economics of Invention: A Survey of the Literature. *The Journal of Business*, 32(2), pp. 101-127

Nelson, R., Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review: Papers and Proceedings*, 61, 69-75

Pablos, P.O.D. (2003). Intellectual Capital Reporting in Spain: A Comparative View, *Journal of Intellectual Capital*, 4(1), pp. 61-81

Peters, R.H., & Taylor, L.A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2), pp. 251-272

Petersen, M.A., & Schoeman, I. (2008). Modeling of Banking Profit via Return-on-Assets and Return-on-Equity. *Proceedings of the World Congress on Engineering*, 2(1), pp. 12-37

Piketty, T. (2014). *Capital in the Twenty-First Century*. Cambridge: Harvard University Press.

Riahi-Belkaoui, A. (2003). Intellectual capital and firm performance of US multinational firms: A study of the resource-based and stakeholder views. *Journal of Intellectual capital*, 4(2), pp. 215-226

Romer, P.M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), pp. 1002-1037

Romer, P.M. (1989). Human Capital and Growth: Theory and Evidence. *National Bureau of Economic Research*, 3173

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 98, pp. 71-102

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, 9(1), pp. 86-136

Rosenthal, E. (1997). Social networks and team performance. *Team Performance Management*

Schiuma G., & Lerro A. (2008). Intellectual capital and company's performance improvement. *Measuring Business Excellence*, 12(2), 3-9

Schultz, T.W. (1961). Investment in Human Capital. *The American Economic Review*, 51(1), pp. 1-17

Sitar, A.S., & Vasić, V. (2005). *Measuring intellectual capital*. Koper: Univerza na Primorskem

Smith, A. (1776). *The Wealth of Nations*. Chicago: The University of Chicago Press

Solow, R.M. (1956). A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics*, 70(1), pp. 65-94

Solow, R.M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, pp. 312-320

Stam, W., Arzlanian, S., & Elfring, T. (2014). Social capital of entrepreneurs and small firm performance: A meta-analysis of contextual and methodological moderators. *Journal of Business Venturing*, 29(1), pp. 152-173

Stewart, T.A. (1995). *Intellectual Capital*. New York: Doubleday

Subramaniam, M., & Youndt, M.A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal*, 48(3), pp. 450-463

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

Tan, H.P., Plowman, D., & Hancock, P. (2007). Intellectual capital and financial returns of companies. *Journal of Intellectual capital*, 8(1), pp. 75-95

Tobin, J. (1969). A General Equilibrium Approach To Monetary Theory. *Journal of Money, Credit and Banking*, 1(1), pp. 15-29

Webster, E., & Jensen, P.H. (2006). Investment in Intangible Capital: An Enterprise Perspective. *The Economic Record*, 82(256), pp. 82-96

Weil, D. (2013). *Economic Growth*. London: Pearson Education.

World Bank. (2007) *Building Knowledge Economies: Advanced Strategies for Development*. Washington: World Bank Publications

Wooldridge, J.M. (2013). *Introductory Econometrics: A Modern Approach*, 6th edition, Boston: Cengage Learning

Youndt, M.A., Subramaniam, M., & Snell, S.A. (2004). Intellectual capital profiles: An examination of investments and returns. *Journal of Management Studies*, 41(2), pp. 335-361

Data Sources

United States Patent and Trademark Office (2021). *Patent Assignment Dataset* [Data set]. https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-assignment-dataset

Wharton Research Data Services. (2018). *MSCI ESG KLD: Social Ratings* [Data set]. https://wrds-www-wharton-upenn-edu.eur.idm.oclc.org/pages/get-data/msci-formerly-kld-and-gmi/msci-esg-kld-stats/social-ratings-full/

Wharton Research Data Services. (2021). *Compustat North America: Fundamentals Annual* [Data set]. https://wrds-www-wharton-upenn-edu.eur.idm.oclc.org/pages/get-data/compustat-capital-iq-standard-poors/compustat/north-america-daily/fundamentals-annual/

8. APPENDIX

Table 7: GICS classification matrix

GICS value	Industry
1	*Energy*
2	*Materials*
3	*Industrials*
4	*Consumer Discretionary*
5	*Consumer Staples*
6	*Health Care*
7	*Financials*
8	*Information Technology*
9	*Communication Services*
10	*Utilities*
11	*Real Estate*

Table 8: VIF analysis comparison

	Original dataset		Revised dataset	
Variables	VIF	1/VIF	VIF	1/VIF
logQ	1.017	.983	1.018	.982
logPROD	1.548	.646	1.578	.634
logXRD	2.864	.349	2.836	.353
logINTAN	12.765	.078		
logPATENT	1.726	.579	1.74	.575
CSR	1.331	.751	1.338	.747
logGDWL	11.943	.084	1.683	.594
AGE	1.592	.628	1.584	.631
REC	1.039	.963	1.039	.963
logSIZE	1.822	.549	1.739	.575
logLEVG	1.211	.825	1.183	.846
2.gics	5.049	.198	4.56	.219
3.gics	8.926	.112	8.032	.125
4.gics	7.799	.128	6.792	.147
5.gics	6.114	.164	5.47	.183
6.gics	9.434	.106	8.365	.12
7.gics	1.165	.859	1.148	.871
8.gics	8.392	.119	7.472	.134
9.gics	1.885	.531	1.702	.587
11.gics	1.316	.76	1.272	.786
Mean VIF	4.447	.	3.187	.

Table 9: results for testing Bond rule-of-thumb

	(1)	(2)
MODELS	FE	Diff. GMM
RoE_{it-1}	0.258***	0.137***
	(0.0155)	(0.00830)
logQ	0.00372	0.00458
	(0.0124)	(0.00322)
logPROD	0.0820***	0.0951***
	(0.00268)	(0.00232)
logXRD	-0.00893**	0.0147**

	(0.00451)	(0.00569)
logPATENT	-0.000126	-0.00116***
	(0.00114)	(0.000396)
CSR	0.0217***	0.00864***
	(0.00823)	(0.00310)
logGDWL	-0.00213	-0.000862
	(0.00143)	(0.00117)
AGE	-0.00423***	-0.00772***
	(0.000476)	(0.000523)
REC	-0.00696*	-0.00607***
	(0.00370)	(0.00100)
logSIZE	0.0159**	0.0185***
	(0.00620)	(0.00637)
logLEVG	-0.00347**	-0.00374***
	(0.00157)	(0.000894)
2.gics	-	
3.gics	-	
4.gics	-	
5.gics	-	
6.gics	-	
7.gics	-	
8.gics	-	
9.gics	-	
11.gics	-	
Constant	0.0813**	
	(0.0355)	
Observations	2,477	2,111
R-squared	0.418	
Number of groups	237	224

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Hypothesis 1 and 3 results using multiple time lags

VARIABLES	(1) RoE	(2) RoA	(3) RG
RoE_{it-1}	0.351***		
	(0.00898)		
RoE_{it-2}	0.00645		
	(0.00544)		
RoA_{it-1}		0.220***	
		(0.00829)	
RoA_{it-2}		0.0219***	
		(0.00444)	
RG_{it-1}			0.161***
			(0.0117)
RG_{it-2}			-0.102***

			(0.00792)
logQ	0.00595	0.00375***	0.0371***
	(0.00384)	(0.00118)	(0.0103)
logPROD	0.0448***	0.0262***	0.00344*
	(0.00131)	(0.000505)	(0.00181)
logXRD	-0.00377***	-0.00382***	0.000449
	(0.000834)	(0.000490)	(0.00124)
logPATENT	-0.00139***	7.76e-05	0.00283***
	(0.000455)	(0.000151)	(0.000699)
CSR	-0.00217	0.00593***	-0.0625***
	(0.00332)	(0.00170)	(0.00596)
logGDWL	-0.00380***	-0.00174***	-0.000597
	(0.000669)	(0.000309)	(0.000822)
AGE	5.28e-05	-6.54e-06	-0.000205***
	(3.75e-05)	(2.14e-05)	(5.09e-05)
REC	-0.0108***	-0.00161***	-0.0509***
	(0.000902)	(0.000389)	(0.00249)
logSIZE	0.0103***	-0.000299	-0.00404***
	(0.00171)	(0.000859)	(0.00150)
logLEVG	0.000466	0.00465***	0.00639***
	(0.00129)	(0.000424)	(0.00178)
2.gics	0.0974***	0.0152**	0.00101
	(0.0161)	(0.00684)	(0.0158)
3.gics	0.107***	0.0305***	0.0126
	(0.0153)	(0.00690)	(0.0150)
4.gics	0.117***	0.0390***	0.0296*
	(0.0164)	(0.00672)	(0.0178)
5.gics	0.0931***	0.0340***	0.0167
	(0.0148)	(0.00706)	(0.0166)
6.gics	0.0733***	0.0221***	0.0313**
	(0.0153)	(0.00680)	(0.0147)
7.gics	-0.0679	-0.0135	0.167
	(0.0467)	(0.0617)	(0.116)
8.gics	0.0741***	0.0220***	0.0292**
	(0.0150)	(0.00738)	(0.0132)
9.gics	0.0206	0.00827	0.0880***
	(0.0170)	(0.00855)	(0.0177)
11.gics	0.0526	0.0131	-0.00551
	(0.0452)	(0.0182)	(0.0526)
Constant	-0.165***	-0.0275**	0.0799***
	(0.0241)	(0.0106)	(0.0250)
Observations	2,323	2,323	2,110
Number of groups	227	227	217

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Hypothesis 4 results using multiple time lags

	(1)	(2)
VARIABLES	RoE	RoA
RoE_{it-1}	0.336***	
	(0.00831)	
RoE_{it-2}	0.00744	
	(0.00488)	
RoA_{it-1}		0.231***
		(0.00813)

RoA_{it-2}		0.0279***
		(0.00440)
logQ	0.00676*	0.0126***
	(0.00364)	(0.00243)
logPROD	0.463***	0.607***
	(0.0166)	(0.0125)
logXRD	-0.118***	-0.197***
	(0.0207)	(0.0271)
logPATENT	-0.0187***	0.0157*
	(0.00695)	(0.00855)
CSR	0.0100	0.0357***
	(0.00750)	(0.00932)
logGDWL	-0.0795***	-0.119***
	(0.0166)	(0.0190)
AGE	0.0346**	-0.00134
	(0.0166)	(0.0186)
REC	-0.101***	-0.0403***
	(0.0101)	(0.00853)
logSIZE	0.119***	-0.00110
	(0.0229)	(0.0280)
logLEVG	0.00680	0.121***
	(0.0167)	(0.0112)
2.gics	0.817***	0.404**
	(0.134)	(0.159)
3.gics	0.877***	0.651***
	(0.135)	(0.157)
4.gics	0.974***	0.861***
	(0.139)	(0.153)
5.gics	0.690***	0.738***
	(0.138)	(0.161)
6.gics	0.556***	0.533***
	(0.122)	(0.150)
7.gics	-0.937**	0.331
	(0.451)	(1.452)
8.gics	0.611***	0.489***
	(0.124)	(0.178)
9.gics	0.173	0.216
	(0.135)	(0.189)
11.gics	0.0623	-0.0833
	(0.378)	(0.373)
Constant	-0.495***	-0.332**
	(0.124)	(0.151)
Observations	2,323	2,323
Number of groups	227	227

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Hypothesis 1 results using composite performance measure

VARIABLES	(1) COMP
$COMP_{it-1}$	0.247***
	(0.00964)
logQ	0.0108***
	(0.00305)
logPROD	0.0357***

	(0.000989)
logXRD	-0.00340***
	(0.000694)
logPATENT	-0.000552
	(0.000340)
CSR	0.00258
	(0.00253)
logGDWL	-0.00324***
	(0.000630)
AGE	6.87e-05**
	(3.37e-05)
REC	-0.00512***
	(0.000806)
logSIZE	0.00530***
	(0.00147)
logLEVG	0.00174*
	(0.000890)
2.gics	0.0598***
	(0.0122)
3.gics	0.0709***
	(0.0115)
4.gics	0.0838***
	(0.0120)
5.gics	0.0681***
	(0.0128)
6.gics	0.0496***
	(0.0116)
7.gics	0.0135
	(0.0528)
8.gics	0.0546***
	(0.0116)
9.gics	0.00750
	(0.0129)
11.gics	0.00408
	(0.0120)
Constant	-0.0939***
	(0.0171)
Observations	2,477
Number of groups	237

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Hypothesis 1 and 3 results excluding Q

VARIABLES	(1) RoE	(2) RoA	(3) RG
RoE_{it-1}	0.316***		
	(0.0101)		
RoA_{it-1}		0.186***	
		(0.00946)	
RG_{it-1}			0.192***
			(0.0127)
logPROD	0.0460***	0.0268***	0.00349*
	(0.00165)	(0.000593)	(0.00198)
logXRD	-0.00394***	-0.00427***	0.000565
	(0.000964)	(0.000614)	(0.00131)

logPATENT	-0.00144**	0.000374*	0.00233***
	(0.000611)	(0.000204)	(0.000709)
CSR	0.000391	0.00778***	-0.0540***
	(0.00379)	(0.00205)	(0.00652)
logGDWL	-0.00373***	-0.00207***	-0.000315
	(0.000913)	(0.000396)	(0.000917)
AGE	0.000114**	2.26e-05	-0.000190***
	(4.76e-05)	(2.78e-05)	(4.90e-05)
REC	-0.0101***	-0.000937**	-0.0538***
	(0.00123)	(0.000453)	(0.00269)
logSIZE	0.00841***	0.000222	-0.00470***
	(0.00196)	(0.00104)	(0.00155)
logLEVG	-0.000782	0.00428***	0.00554***
	(0.00154)	(0.000437)	(0.00163)
2.gics	0.0925***	0.0113	0.00321
	(0.0153)	(0.00885)	(0.0166)
3.gics	0.101***	0.0261***	0.0115
	(0.0149)	(0.00875)	(0.0157)
4.gics	0.117***	0.0358***	0.0320*
	(0.0159)	(0.00916)	(0.0180)
5.gics	0.0860***	0.0286***	0.0161
	(0.0176)	(0.00906)	(0.0173)
6.gics	0.0699***	0.0192**	0.0296*
	(0.0147)	(0.00870)	(0.0152)
7.gics	-0.0828	0.0135	0.143
	(0.0715)	(0.0730)	(0.161)
8.gics	0.0722***	0.0217**	0.0213
	(0.0147)	(0.00900)	(0.0140)
9.gics	0.0120	0.00629	0.0720***
	(0.0172)	(0.00944)	(0.0187)
11.gics	0.0146	-0.0158*	-0.000349
	(0.0155)	(0.00883)	(0.0639)
Constant	-0.142***	-0.0249*	0.0754***
	(0.0224)	(0.0137)	(0.0250)
Observations	2,477	2,477	2,276
Number of groups	237	237	227

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Hypothesis 2 results excluding Q

	(1)	(2)	(3)	(4)
VARIABLES	RoE (2 years)	RoA (2 years)	RoE (5 years)	RoA (5 years)
FUTURE2RoE $_{it-1}$	0.839***			
	(0.0808)			
FUTURE2RoA $_{it-1}$		0.0975***		
		(0.0124)		
FUTURE5RoE $_{it-1}$			0.789***	
			(0.0806)	
FUTURE5RoA $_{it-1}$				0.0620***
				(0.0101)
logPROD	-0.00229	0.00543***	-0.0115***	0.00311**
	(0.00290)	(0.000942)	(0.00363)	(0.00125)
logXRD	0.0121***	-0.00330**	0.0174***	-0.00218*
	(0.00267)	(0.00126)	(0.00273)	(0.00130)
logPATENT	-0.00700***	0.00119	-0.0101***	-0.000751

	(0.00212)	(0.000733)	(0.00204)	(0.000890)
CSR	0.0365***	0.0219***	0.0104	0.0271***
	(0.0114)	(0.00498)	(0.0145)	(0.00610)
logGDWL	-0.000555	0.00288**	-0.00624**	0.00135
	(0.00241)	(0.00115)	(0.00240)	(0.00115)
AGE	3.68e-05	-8.51e-05**	1.82e-05	-8.70e-05*
	(0.000115)	(4.16e-05)	(9.79e-05)	(4.51e-05)
REC	0.0149***	0.00814***	0.00240	0.00179
	(0.00317)	(0.00136)	(0.00268)	(0.00133)
logSIZE	0.00923**	-0.00676***	0.0121***	-0.00488***
	(0.00362)	(0.00152)	(0.00383)	(0.00148)
logLEVG	-0.00610**	0.00311***	-0.00431*	0.00302***
	(0.00284)	(0.00106)	(0.00256)	(0.00109)
2.gics	-0.0615	-0.0959***	0.0727**	-0.0700***
	(0.0488)	(0.0233)	(0.0357)	(0.0193)
3.gics	-0.0597	-0.0874***	0.0714*	-0.0554***
	(0.0480)	(0.0237)	(0.0386)	(0.0203)
4.gics	-0.0275	-0.0625***	0.0604*	-0.0413**
	(0.0475)	(0.0227)	(0.0358)	(0.0174)
5.gics	-0.0227	-0.0759***	0.0909**	-0.0460**
	(0.0477)	(0.0228)	(0.0399)	(0.0192)
6.gics	-0.107**	-0.0791***	0.00547	-0.0571***
	(0.0440)	(0.0227)	(0.0335)	(0.0184)
8.gics	-0.0959**	-0.0678***	0.0337	-0.0374**
	(0.0456)	(0.0216)	(0.0339)	(0.0177)
9.gics	-0.123	-0.217**	0.156	-0.148*
	(0.164)	(0.0860)	(0.179)	(0.0838)
11.gics	-0.369**	-0.176***	-0.0808	-0.104**
	(0.177)	(0.0641)	(0.0996)	(0.0443)
Constant	0.0854	0.181***	-0.00188	0.162***
	(0.0640)	(0.0294)	(0.0538)	(0.0241)
Observations	863	863	863	863
Number of groups	111	111	111	111

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Hypothesis 4 results excluding Q

	(1)	(2)
VARIABLES	RoE	RoA
RoE_{it-1}	0.304***	
	(0.00976)	
RoA_{it-1}		0.191***
		(0.00920)
logPROD	0.478***	0.624***
	(0.0179)	(0.0158)
logXRD	-0.141***	-0.205***
	(0.0243)	(0.0323)
logPATENT	-0.0110	0.0160
	(0.0126)	(0.0110)
CSR	0.00172	0.0481***
	(0.00964)	(0.0111)
logGDWL	-0.0737***	-0.125***
	(0.0215)	(0.0254)
AGE	0.0651***	0.00737
	(0.0211)	(0.0244)

REC	-0.106***	-0.0228**
	(0.0121)	(0.00962)
logSIZE	0.114***	-0.00956
	(0.0266)	(0.0337)
logLEVG	-0.0157	0.113***
	(0.0192)	(0.0129)
2.gics	0.882***	0.265
	(0.145)	(0.206)
3.gics	0.978***	0.551***
	(0.144)	(0.208)
4.gics	1.114***	0.807***
	(0.144)	(0.207)
5.gics	0.751***	0.629***
	(0.164)	(0.209)
6.gics	0.681***	0.474**
	(0.135)	(0.203)
7.gics	-1.331**	-0.624
	(0.659)	(1.573)
8.gics	0.793***	0.432**
	(0.141)	(0.214)
9.gics	0.347**	0.173
	(0.157)	(0.226)
11.gics	0.141	-0.353*
	(0.144)	(0.207)
Constant	-0.612***	-0.243
	(0.133)	(0.196)
Observations	2,477	2,477
Number of groups	237	237

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Hypothesis 1 and 3 results when using year dummies

	(1)	(2)	(3)
VARIABLES	RoE	RoA	RG
RoE_{it-1}	0.329***		
	(0.0107)		
RoA_{it-1}		0.193***	
		(0.0118)	
RG_{it-1}			0.222***
			(0.0177)
logQ	0.00271	0.00519***	0.00968
	(0.00425)	(0.00146)	(0.0102)
logPROD	0.0392***	0.0257***	0.00662***
	(0.00188)	(0.000688)	(0.00210)
logXRD	-0.00702***	-0.00579***	-0.000498
	(0.00116)	(0.000533)	(0.000993)
logPATENT	-0.00249**	0.000249	0.000633
	(0.000972)	(0.000463)	(0.000716)
CSR	0.0232***	0.0155***	-0.0165***
	(0.00483)	(0.00207)	(0.00583)
logGDWL	-0.00306***	-0.00137***	-0.000665
	(0.000866)	(0.000368)	(0.000875)
AGE	0.000159***	7.17e-08	-0.000284***
	(5.08e-05)	(2.27e-05)	(3.54e-05)
logSIZE	0.00913***	0.00116	-0.00412***

	(0.00196)	(0.000745)	(0.00116)
logLEVG	-0.000821	0.00379***	0.00306**
	(0.00183)	(0.000468)	(0.00118)
2001	0.0141**	0.00135	
	(0.00545)	(0.00185)	
2002	0.0199***	0.00182	-0.0519***
	(0.00366)	(0.00147)	(0.00830)
2003	0.0190***	0.00169	-0.0127**
	(0.00344)	(0.00133)	(0.00550)
2004	0.0177***	0.00292**	0.00810
	(0.00334)	(0.00117)	(0.00500)
2005	0.0206***	0.00234**	-0.0247***
	(0.00362)	(0.00110)	(0.00364)
2006	0.0222***	0.00219**	-0.0135***
	(0.00350)	(0.00101)	(0.00463)
2007	0.0308***	0.00202**	-0.0130***
	(0.00317)	(0.000870)	(0.00424)
2008	0.0187***	0.00218**	-0.0358***
	(0.00299)	(0.000927)	(0.00367)
2009	-0.00353	-0.00363***	-0.123***
	(0.00244)	(0.000886)	(0.00597)
2010	0.0234***	0.00252***	0.0141**
	(0.00234)	(0.000716)	(0.00605)
2011	0.0141***		
	(0.00229)		
2012	0.00232	-0.00558***	-0.0574***
	(0.00195)	(0.000658)	(0.00452)
2013		-0.00479***	-0.0513***
		(0.000840)	(0.00477)
2014	0.00790***	-0.00549***	-0.0355***
	(0.00166)	(0.000956)	(0.00485)
2015	0.00832***	-0.00724***	-0.0797***
	(0.00271)	(0.00109)	(0.00558)
Constant	-0.0471***	-0.000535	0.129***
	(0.0158)	(0.00609)	(0.0106)
Observations	2,477	2,477	2,276
Number of groups	237	237	227

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Hypothesis 2 results when using year dummies

VARIABLES	(1) RoE (2 years)	(2) RoA (2 years)	(3) RoE (5 years)	(4) RoA (5 years)
FUTURE2RoE $_{it-1}$	0.929***			
	(0.0682)			
FUTURE2RoA $_{it-1}$		0.107***		
		(0.0123)		
FUTURE5RoE $_{it-1}$			0.843***	
			(0.0792)	
FUTURE5RoA $_{it-1}$				0.0688***
				(0.0108)
logQ	-0.0203	-0.0207***	0.00278	-0.0112**
	(0.0184)	(0.00581)	(0.0144)	(0.00565)
logPROD	-0.00500	0.00812***	-0.0130***	0.00613***
	(0.00324)	(0.00110)	(0.00388)	(0.00121)

logXRD	0.00920***	-0.00128	0.0120***	-0.00110
	(0.00199)	(0.000931)	(0.00250)	(0.000890)
logPATENT	-0.00840***	-0.000408	-0.00827***	-0.000850
	(0.00200)	(0.000880)	(0.00190)	(0.000853)
CSR	-0.00118	0.0203***	-0.00769	0.0215***
	(0.0118)	(0.00490)	(0.0142)	(0.00532)
logGDWL	-0.00112	-0.000780	-0.00423***	-0.000617
	(0.00192)	(0.000737)	(0.00158)	(0.000745)
AGE	0.000228**	-0.000136***	0.000307***	-9.23e-05*
	(9.41e-05)	(4.18e-05)	(9.43e-05)	(4.72e-05)
logSIZE	0.0114***	-0.00301**	0.0121***	-0.00296**
	(0.00294)	(0.00119)	(0.00342)	(0.00130)
logLEVG	-0.00554*	0.00484***	-0.00562*	0.00297***
	(0.00285)	(0.00102)	(0.00310)	(0.00108)
2001	-0.00882	-0.000919	0.0201**	0.0135***
	(0.00687)	(0.00287)	(0.00881)	(0.00256)
2002	-0.0151***	0.00502**	0.0297***	0.0113***
	(0.00523)	(0.00230)	(0.00781)	(0.00244)
2003	-0.00350	0.00642***	0.0144*	0.00457*
	(0.00460)	(0.00178)	(0.00859)	(0.00253)
2004	-0.0108**	0.00149	-0.0264***	-0.0115***
	(0.00522)	(0.00159)	(0.00575)	(0.00293)
2005			0.0222***	0.00691***
			(0.00510)	(0.00182)
2006	-0.0266***	-0.00484**	0.0102***	0.00412**
	(0.00579)	(0.00194)	(0.00334)	(0.00171)
2007	-0.0451***	-0.0114***		
	(0.00557)	(0.00236)		
2008	0.00145	0.00624***	0.00571	0.00338**
	(0.00552)	(0.00211)	(0.00422)	(0.00152)
2009	-0.00934	0.00262	0.0139***	0.00438***
	(0.00598)	(0.00221)	(0.00407)	(0.00166)
2010	-0.0211***	-0.00604**	0.0241***	0.000258
	(0.00598)	(0.00232)	(0.00698)	(0.00292)
Constant	0.0260	0.0799***	0.0220	0.0868***
	(0.0283)	(0.0128)	(0.0307)	(0.0125)
Observations	863	863	863	863
Number of groups	111	111	111	111

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Hypothesis 4 results when using year dummies

VARIABLES	(1) RoE	(2) RoA
RoE_{it-1}	0.324***	
	(0.0103)	
RoA_{it-1}		0.195***
		(0.0101)
logQ	0.00538	0.0114***
	(0.00385)	(0.00300)
logPROD	0.407***	0.587***
	(0.0186)	(0.0185)
logXRD	-0.179***	-0.254***

	(0.0289)	(0.0311)
logPATENT	-0.0347*	-0.00903
	(0.0182)	(0.0207)
CSR	0.0562***	0.0866***
	(0.0104)	(0.0108)
logGDWL	-0.0499**	-0.101***
	(0.0217)	(0.0239)
AGE	0.0616***	0.0159
	(0.0186)	(0.0215)
logSIZE	0.101***	0.00603
	(0.0248)	(0.0227)
logLEVG	-0.00832	0.102***
	(0.0223)	(0.0137)
2001	-0.0316	-0.0506
	(0.0445)	(0.0370)
2002	0.0470	-0.0148
	(0.0336)	(0.0317)
2003	0.0435	-0.000180
	(0.0299)	(0.0273)
2004	0.0238	0.0307
	(0.0244)	(0.0257)
2005	0.0554***	0.0154
	(0.0212)	(0.0226)
2006	0.0681***	0.0356
	(0.0249)	(0.0224)
2007	0.135***	0.0264
	(0.0206)	(0.0194)
2008	0.0388*	0.0321
	(0.0227)	(0.0201)
2009	-0.179***	-0.112***
	(0.0184)	(0.0178)
2010	0.0757***	0.0420***
	(0.0124)	(0.0145)
2012	-0.105***	-0.136***
	(0.0196)	(0.0163)
2013	-0.137***	-0.113***
	(0.0205)	(0.0200)
2014	-0.0725***	-0.144***
	(0.0206)	(0.0193)
2015	-0.0774***	-0.167***
	(0.0273)	(0.0236)
Constant	0.231***	0.301***
	(0.0226)	(0.0236)
Observations	2,477	2,477
Number of groups	237	237

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Hypothesis 2 results using one and eight year future performance

	(1)	(2)	(3)	(4)
VARIABLES	RoE (1 year)	RoA (1 year)	RoE (8 years)	RoA (8 years)
FUTURE1RoE $_{it-1}$	0.353***			
	(0.0526)			
FUTURE1RoA $_{it-1}$		0.590***		
		(0.0664)		

FUTURE8RoE $_{it-1}$			0.241	
			(0.307)	
FUTURE8RoA $_{it-1}$				-0.00491
				(0.677)
logQ	-0.0188	-0.0213***	0.206**	0.0631*
	(0.0163)	(0.00755)	(0.101)	(0.0362)
logPROD	-0.00843*	-0.00568**	-0.0343	-0.00477
	(0.00462)	(0.00264)	(0.0371)	(0.0233)
logXRD	0.0111***	0.00125	0.00351	-0.000753
	(0.00216)	(0.000980)	(0.0356)	(0.0203)
logPATENT	-0.00499***	-0.00101*	0.000299	0.00247
	(0.00187)	(0.000554)	(0.0124)	(0.00563)
CSR	0.0144	0.00436	0.117*	0.0463*
	(0.0135)	(0.00531)	(0.0598)	(0.0263)
logGDWL	0.00113	0.000623	0.0119	0.00597
	(0.00185)	(0.000753)	(0.0294)	(0.0153)
AGE	0.000162	4.53e-05	8.52e-05	-7.89e-05
	(0.000119)	(3.70e-05)	(0.000724)	(0.000470)
REC	-0.0228***	-0.00387**		
	(0.00388)	(0.00149)		
logSIZE	0.00327	-0.00249**	-0.00503	-0.0104*
	(0.00314)	(0.00102)	(0.0198)	(0.00607)
logLEVG	0.00223	0.00234***	-0.00761	-0.000968
	(0.00230)	(0.000889)	(0.0161)	(0.00666)
2.gics	-0.0463	-0.0293***	-0.328	-0.169
	(0.0298)	(0.0104)	(0.748)	(0.366)
3.gics	-0.0542*	-0.0308***	-0.346	-0.162
	(0.0299)	(0.0100)	(0.727)	(0.365)
4.gics	0.00820	-0.0179	-0.268	-0.105
	(0.0303)	(0.0112)	(0.721)	(0.388)
5.gics	0.00820	-0.0139	-0.258	-0.120
	(0.0307)	(0.0108)	(0.742)	(0.385)
6.gics	-0.0551*	-0.0210**	-0.331	-0.137
	(0.0304)	(0.00959)	(0.645)	(0.336)
8.gics	-0.0476	-0.0132	-0.323	-0.130
	(0.0322)	(0.00926)	(0.580)	(0.296)
9.gics	0.178	0.109		
	(0.225)	(0.0847)		
11.gics	-0.329**	-0.134*	-0.968	-0.387
	(0.159)	(0.0680)	(1.991)	(1.034)
Constant	0.0929**	0.0812***	0.516	0.294
	(0.0417)	(0.0151)	(0.820)	(0.363)
Observations	761	761	122	122
Number of groups	111	111	79	79

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1