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Innovation Workers and Firm Performance - The Impact of Individual-Level Knowledge Diversity and Experience

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Gothenburg, Sweden 2017

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Abstract

A large body of literature has emerged with economists and managers seeking to understand how firms shall utilize their resources to ensure competitive advantage and satisfying performance. Scholars have been attempting to identify which resources are most valuable, and have argued for the vital role played by knowledge in producing innovation and enabling well-performing firms. This stance has been born through the theories of knowledge-based view and has grown to be acknowledged by academia and industry alike. However, the theory has been criticized for inadequately understanding the role of the individuals inhabiting the firms. This research seeks to quantitatively understand how variations in individual-level knowledge may impact the market value of firms. Forming an understanding regarding the depth and breadth of inventors' experience through analyzing the number of companies, industries, and technologies they have previously worked in. By collecting information derived from a vast amount of patents, firms receives an accumulated score based on all employed inventors' experiences and further used to understand its impact. Finally, the study employs several regression models on panel data to identify the relationship between individual-level knowledge and firm performance. The results show that individual-level company- and technology diversity have a negative effect on market value, whereas industry diversity has a positive effect. Furthermore, the quality and quantity of the inventor's patent experience have a significant positive effect on market value. These findings lead to the conclusion that caution should be taken when considering the individual-level functional diversity amongst innovation workers, while their experience and its quality contribute to the performance of the firm.

Keywords: individual-level functional diversity, innovation production, patent experience, firm performance, knowledge-based view, panel data, regression test

Acknowledgements

We extend our gratitude to our supervisor Johan Brink for providing us with valuable insight, and for supporting us through this research project. We also thank our lecturer Daniel Ljungberg for his feedback and for providing us with assistance to successfully conduct this study. We would like to thank the PhD student Snöfrid Börjesson Herou for dedicating a piece of her time into helping us in the project.

Rasmus Lindgren and Philip Masek, Gothenburg, Sweden 2^{nd} of June 2017

Contents

1

Introduction

During the past two decades, knowledge has been increasingly important for business organizations to survive in the environment of hardening competition. New concepts, such as the *"knowledge economy"*, emphasizes a shift from tangible to intangible assets as the most strategically important resource of a firm. Increasing demand for knowledge-intensive products and services has turned the attention to intellectual assets as the primary tool to achieve economic benefits (Chandler & Munday, 2011). In management literature, this circumstance is reflected in the increased interest in the knowledge-based view (KBV), a developed version of the older resource-based view, claiming knowledge to be the most important strategic resource for a company to possess (Akhavan & Pezeshkan, 2014; Faulkner & Campbell, 2006; Mjahed Hammami & Triki, 2011; Nonaka, Von Krogh, & Voelpel, 2006). Supporters of the KBV argue knowledge to be the intangible resource which allows a firm to combine and utilize other resources in a unique way, differentiating the company from its competitors and therefore creating conditions for long-term competitive advantage (Akhavan & Pezeshkan, 2014; Mjahed Hammami & Triki, 2011; Nonaka, Von Krogh, & Voelpel, 2006).

The innovation process could be described as the link between existing knowledge and competitive advantage. Firms can supply the market with new and unique products and services and thereby capitalize the intellectual assets by developing new knowledge from existing knowledge, or by combining knowledge in new ways (Grant, 2016). In an increasingly global business environment with intense competition, companies must innovate and renew their offering to stay relevant on the market (Schilling, 2005). As an essential element of innovation, the importance of knowledge has increased due to its vital role in creating wealth in the modern knowledge economy (Burnett, 2012).

In response to the growing importance of innovation, comprehensive academic efforts have been made to understand, as well as develop theoretical frameworks in the field. Considerable research is aimed to map the conditions and circumstances under which innovation processes generate the best results. In a strive to understand why certain organizations consistently outperform others, concepts such as knowledge flows, group management for creativity, and experience have been born (Felin & Hesterly, 2007).

A company's success to profit from its innovations depends on two things, first, the total value created by the innovation and, second, the share of that value appropriated by the firm. Property rights play a significant role in securing returns from a company's innovations, where the oldest and perhaps the most well-known kind of protection are patents Grant (2016). Due to its global use, legal status and bibliographic nature, patents provide a unique possibility to gather and analyze detailed information regarding inventions. They can be considered as paper tracks and can be used to trace an inventor's past activity by observing the inventor's registered patents (Aldieri & Vinci, 2016). Examining their previous patent involvement allows the observer to detect specific characteristics that could help to develop an understanding regarding critical components for successful innovations.

1.1 Purpose of the study

The purpose of this study is to examine how theories regarding diversity and experience of individuals, in the context of innovative performance, holds in a real-world setting. This makes for an interesting exploration of how previous experiences of individuals impact the innovative performance of firms - understanding the role of diversity and experience. This study has failed to identify a vast amount of extensive research which seeks to quantitatively gather empirics to confirm the relations between individuals' experience and diversity characteristics.

This research aims to understand the relationship between firm performance and individuals' knowledge characteristics through the application of an extensive quantitative research study. Primarily, the study bases its merits on previous researchers invitation for continued investigation within the topics of knowledge characteristics and firm performance. Erden, Klang, Sydler, and von Krogh (2014) argues for the need of additional examination of individual-level knowledge variables to understand their impact on firm performance. The authors suggest that current literature criticizes KBV for paying limited attention to individual-level variables (Felin & Hesterly, 2007). This invitation motivate for why this study is relevant to conduct.

1.2 Research gap

Despite a growing interest in knowledge, its role as a source of innovation and an enabler of long-term competitive advantage, research has been relatively focused on firm-level characteristics of knowledge management. In contrast, there has been little attention given to individual-level variables (DeCarolis & Deeds, 1999). Felin and Hesterly (2007) takes a further stand in this debate, arguing that the knowledge-based view is too concerned in trying to explain value-creation using the collective as a source, a statement which also finds support from Grant (1996). Taking a collectivistic approach as the key level of analysis is the same thing as making an implicit assumption of homogeneity at the lower levels of analysis, the individuals together constituting the collective (Felin & Hesterly, 2007). In contrast, there is research pointing in a direction where the innovative output has a much more direct connection to the presence of certain individuals. Ernst (2001) studied acquisitions made by 43 German companies and found that the success of such mergers is highly dependent on whether R&D personnel chooses to stay in the firm. In situations where key inventors, individuals with high performance in both quality and quantity of patents, left the acquired company or were moved to other positions, the innovative output dropped for the whole acquired organization. According to Felin and Hesterly (2007), other studies have seen similar observations where acquired companies have failed to deliver new value after a loss of key scientists. These indications of the importance of knowledge at the individual level give additional fuel for the discussion about the most suitable level for analyzing the locus of innovation.

The aim to find the locus of knowledge and the source of new value is closely related to strategic management. The raison d'être of strategic management is to explain and compare performance heterogeneity to its different sources. The field has previously taken different approaches, and the search for a suitable level of analysis has taken several directions. Early studies have usually had a focus on industries while they failed to take firm-level factors into account, and consequently drew conclusions that overestimated the importance of industry specific factors on performance. Today's firm-level focus is suspected to suffer from a similar type of failure, namely a too narrow scope that carries a risk of neglecting the influence of individual-level factors. Empirically, it is not possible to make scientific claims about collective competencies and knowledge while not accounting for individuals (Felin & Hesterly, 2007).

1.3 Research question

What impact does functional diversity and experience amongst patent inventors have on the market performance of firms?

1.4 Contribution

This research seeks to build an understanding of what impact individual-level knowledge factors have on a firm's market value. Research have criticized the widely adopted concept of knowledge-based for its lack of individual-level aspects, which argues for a significant research gap (Felin & Hesterly, 2007). This study aims to fill this gap by answering the research question. Answering the questions will be done by providing an annual scoring for firms based on a portion of their employed inventors. The score directly reflects individual inventors' previous experience before filing a patent application at the company which receives a score. This approach will shed light on, and bring a general understanding about, some of the aspects regarding value-creating knowledge factors on an individual level.

1.5 Structure of the report

Chapter 2 provides a background presenting broad economic and strategic management theories. The background section aims at building a comprehensive understanding of the general context within which this study operate, and the general concepts used. It furthers seeks to frame the path between individual-level knowledge and firm performance. The framing is done by first explaining the general concepts and characteristics of knowledge; its critical role in creativity, innovation, and patent production; and subsequently its impact on firm performance. Each step brings a comprehensive overview of the literature regarding the definitions of related concepts respectively.

Chapter 3 contains the theoretical framework which provides an extensive understanding of individual-level knowledge concepts contributing to the innovation process. Namely, the concepts of creativity, diversity, and experience, where the last two concepts are in focus for this study. Creativity plays the role of explaining how knowledge diversity may contribute to the innovation process. Experience demonstrates how knowledge develops over time and adds to value-creating activities. This section presents the construction of the hypotheses employed to answer the research question regarding the relevant theories. Chapter 4 presents the methodology which explains the steps taken to arrive at the results used for testing the hypotheses and answering the research question. This section describes the step-wise process, the data used, and the limitations of the study.

Chapter 5 holds the results which present the raw results generated from executing the method.

Chapter 6 a discussion is held which seeks to analyze the results provided by the previous section. The discussion is carried out by linking the results to previous literature presented in the theoretical framework. The aim is to formulate an understanding of the studied subject by interpreting the results and consequently answer the research question.

Finally, chapter 7 and 8 contains conclusions and future work respectively. These sections firstly provides a conclusion of this study in its entirety, and secondly the identification of relevant future work related to this study.

2

Background

Striving to understand characteristics of firms have been a target of great interest for management researchers for a long time. Theories in economics, usually address firm-performance, structures, behaviors, and differences by putting their focus on explaining how firms perform on markets. Different scientific disciplines make various contributions to the understanding where organizational theory describes the complex relations between individuals, units, and departments while neoclassical economics use equilibrium analysis as a starting point to understand and predict a firm's decisions in supply and purchases. Strategic management combines several research fields to explain differences in performance between companies, which this chapter will aim to present in further detail.

2.1 Economic theories of the firm

It is of interest to build an understanding regarding the factors which are considered crucial for firm performance. Thus an investigation of the historical development of economics will provide a narrative leading up to the current state of theories and literature relating to these determining factors. This section seeks to clarify the standpoints and to present different beliefs about competitive advantage and firm performance.

In the early 20th century, theories of neoclassical economics became gained popularity for explaining market dynamics and industrial economics. These theories regard the market as being driven by the distribution of goods, outputs, and inputs through supply and demand. The firm is considered to always produce at a level which maximizes profits as a response to the present state of the market. This view assumes that the individuals residing, and driving, the firm will make fully informed and rational economic decisions (Weintraub, 1993). Neoclassical economics, although its widespread adoption, has been criticized for its utopian assumptions. Many scholars believe that the theory draws excessively unrealistic assumptions regarding the environment in which individuals and firms operate. Hart (1995) criticizes the theory for ignoring issues existing within the company. He further criticizes that the firm is treated as a perfectly efficient apparatus which will output as to having maximized profits in regards to the market environment at all times, where everything is operating perfectly smoothly, and no organizational hitches occur. Coinciding with the theories of neoclassical economics, Veblen (1898) criticizes the same unrealistic assumptions of human behavior, taunting the theories' *"... hedonistic conception of man as that of a lightning calculator of pleasures and pains"*. More contemporary theories have been born from the cracks of neoclassical economics, as it largely disregards the complex constructs existing within firms. More recently, behavioral economics have taken form, responding to the narrow conceptions of human behavior in neoclassical economics. As an example, Simon (1955) presents the theory of bounded rationality which tackles the unrealistic utopia given by neoclassical economics. Bounded rationality argues that decisions are confined to the limits of information, cognitive limitations of the mind, and the finite amount of time individuals have within the firm. Thus, behavioral economics additionally consider firm performance as dependent on firm-specific factors such as the characteristics of the organization and its actors.

Conclusively, economic theory has over time built diverging viewpoints of the environment within which firms and individuals operate. Spanning from exogenous market forces found in neoclassical economics, to endogenous firm factors in behavioral economics. Each theory is taking a different stance regarding the factors which are believed critical to include when examining firm performance. The previously mentioned theories introduce an ideological understanding of economic standpoints regarding the topic. To further expand on firm performance, the strategic management discipline presents a utilitarian, and more explicit, discussion of determining factors which allow companies to gain competitive advantage, and thus improving their performance.

Strategic management presents the resources-based view (RBV) which is considered one of the more prominent and accepted theoretical frameworks regarding competitive advantage. This theoretical framework discusses how firms can achieve competitive advantage by efficiently utilize their resources.

More specifically, the framework argues that firms can maintain their competitive advantage over time, by having well-calculated processes and strategic routines in place, to efficiently and effectively manipulate their tangible assets (Barney, 1991; Nelson, 1991; Penrose, 1959; Peteraf, 1993; Prahalad, 1990; Schumpeter, 1934; Teece, Pisano, & Shuen, 1997; Wernerfelt, 1984). The RBV is different from previous theories in the way it articulates the importance of unique and cumulative capabilities at the firm level to create value. By stressing the relevance of unique capabilities, the resource-based view has stimulated an interest in intangible resources, which has further expanded itself into the knowledge-based view. The most important aspect of this theory is the focus on knowledge, which is regarded as the most valuable resource for firms to gain competitive advantage (DeCarolis & Deeds, 1999; Erden, Klang, Sydler, & von Krogh, 2014).

2.2 Knowledge-based view

The knowledge-based view begun in the early 1990's, as some research streams and ideas converged into what is now commonly referred to as *"the knowledge-based view of the firm"*. The theory was not brand-new, it was rather a collection of several existing exploratory studies with different aspects of companies and organizations, where they share the focus on knowledge and its impact on production and trade. In this regard, the KBV is a set of ideas unifying scientific findings in some related fields such as knowledge-based competition, knowledge transfer, learning, creativity, new product development, and interfirm collaboration (Grant, 2016). A central argument of the knowledge-based view is that companies' knowledge bases and capabilities are the most important determinants to explain how firms perform differently. As a consequence, the more rare and valuable the knowledge a company possesses is, the better it will perform in comparison to its competitors (Arend, Patel, & Park, 2014). With knowledge becoming more critical in creating and sustaining competitive advantage, organizations will face new challenges in developing capabilities to identify, capture, create, and absorb knowledge (Wang & Wang, 2012).

"The New Economy" is a term used to describe the post-industrial and knowledge-based economy. While the agrarian economy considered land as the most prominent resource in production, the industrial economy was dependent on capital, labor, and equipment. In contrast, the new economy recognizes intellectual assets, particularly knowledge, as the most critical resource (Wang & Wang, 2012). Furthermore, there also exists a difference in its recognition of intangible, rather than tangible assets. Which in regards to input and output results in a shift from goods to services, and an increased importance of more abstract assets such as brands and technology, rather than financial and physical assets. A manifestation of greater attention given to intangible assets such as knowledge can be found the increasing gap between market value and booked value of companies, where the booked value is nowadays accounting for less of the market value (Grant, 2016).

Since the 1980's, the idea of the firm as a body of knowledge has had considerable attention among corporate strategy theorists. Firm-specific knowledge has been pointed out as the critical asset responsible for performance differences by arguing that tangible resources always have their origin outside the company and consequently should not be enough to explain why some firms succeed to achieve long-term competitive advantage and outperform competitors. A company's knowledge allows it to add value to input factors in a unique way and thereby differentiating it from its competitors (Spender, 1996).

Spender (1996) argues that organizations evolve by adapting their body of knowledge embodied in employees, which is a process that, to a high degree, takes place at a tacit level. Furthermore, this view identifies the firm as an interacting entity of knowledge systems where routines and practices interact with tacit knowledge (Reihlen & Ringberg, 2013). Spender (1996) suggests that organizational knowledge exists on different levels. Except for the division into tacit and explicit knowledge, the author further makes a distinction between individual and social level knowledge. Where social level knowledge exists in organizational practice, implicitly, and deeply embedded in collective interactions and experiences (Reihlen & Ringberg, 2013; Spender, 1996). The tacit aspect makes collective knowledge difficult to define and transfer, as it becomes hard to isolate from its context even though employees are the carriers within whom it exists (Reihlen & Ringberg, 2013). Spender (1994) brings further clarity to the issue by stating that much of the collective knowledge is hard to pronounce outside the situation of its application but is rather uncovered when an individual engages in collective practice. Furthermore, to illustrate the synergetic benefits of organizations and to relate the collective knowledge and its potential to that of the individuals, Spender (1994) uses the following metaphor: *"An ordered library offers systemic possibilities, such as rapid search, selection, and aggregation, that cannot be explained by looking at the books themselves. These opportunities only exist because of the investment made in defining and creating interrelations between the books, their physical arrangement and the catalogs"*.

To explain how new knowledge is developed inside the organization's socio-cultural knowledge system, Spender (1994) uses the intuition concept which could be defined as creating or extracting knowledge. Recognized as a cognitive process not deliberately using explicit knowledge but rather a subconscious use of internalized tacit knowledge systems. By tacit interaction of the organization's knowledge systems, tacit knowledge is converted to explicit and is expressed in unique organizational practices (Reihlen & Ringberg, 2013).

Criticism has been raised to the KBV for its assumptive view on knowledge at a firm level. There exists a clear risk of obscuring the individual's contribution to the creation, storage, and deployment of knowledge taking a firm-level approach when analyzing. Knowledge is defined as the creation of rules, procedures, and norms when taking the organization as a starting point in the analysis. However, such an approach will fail to pay attention to lower-level individual parameters, and limited explanation will be found on how management should be practiced to influence the processes of interactions between individuals, which is considered the foundation of organizational knowledge production (Grant, 1996). Applying a more aggregated filter to observe the firm as a knowledge producer, the fundamental common denominator of knowledge production is the individual. All knowledge creation is based on the individual's activity, and the role of a firm is to provide a setting where individuals specialized in different fields can employ their knowledge and transform it into products and services. Consequently, putting the individual in the center of knowledge and knowledge production is not the same as denying the importance of the organization, but should rather be seen as a compliment to that approach, intended to establish a complete understanding (Grant, 1996). When the level of complexity is high as within technological innovation, the process often requires specialists in several fields to combine their knowledge in a joint effort (Runiewicz-Wardyn, 2013). In this process, the organization plays a vital role in combining and integrating an individual's knowledge with that of another, providing suitable incentives, and to coordinate the work towards a common goal.

Despite that Spender (1994, 1996) acknowledges the role of employees as carriers supporting the collective knowledge system, the assumption of an overriding tacit social knowledge system that seems to exist apart from the individual is criticized for underplaying the role of the individual. In this context, the cognitive contribution made by individuals to the organization gets lost (Reihlen & Ringberg, 2013). Close to this recognition of an incomplete framework from the aspect of admitting the individual's role is research claiming the human capital to be the source of competitive advantage.

Campbell, Coff, and Kryscynski (2012) emphasizes the human capital to be at the core of competitive advantage, but only under circumstances where it is rare, valuable, and could be retained from competitors. Firm-specific human capital refers to employees' knowledge and skills that are only relevant in the context of a specific firm, and for that reason difficult to apply in other firms. In contrast to general human capital, which is easily transferred, firm-specific human capital limits the mobility of employees and consequently serves as an isolating mechanism protecting valuable knowledge and contributing to sustained competitive advantage. The firm-specific dimension of a worker's knowledge applies to two mechanisms of protection. First, due to limited applicability of that knowledge in another firm, an individual carrying this kind of knowledge is less likely to get the same appreciation elsewhere and is for that reason not as obvious as a target for recruitment by competitors. Secondly, even if such an employee leaves for another firm the damage will be attenuated by the low applicability of firm-specific knowledge in the context of a competing firm. However, an implication of this view is that an individual's knowledge is neither black or white. The authors suggest that an individual's knowledge should be regarded as a portfolio consisting both firm-specific and general knowledge. Consequently, the value of an individual's general knowledge, in the eyes of a competing firm, sometimes exceeds that of firm-specific knowledge expressed through salary. This circumstance implies that a high degree of firm-specific knowledge, embodied in an individual, is not always enough to prevent valuable knowledge to leak out of a firm (Campbell, Coff, & Kryscynski, 2012).

2.3 The concept of knowledge

As the KBV suggests, knowledge itself holds great value and is becoming increasingly important for the success of firms (Grant, 1996). However, to fully understand what knowledge entails, a definition of the knowledge concept is required. This section seeks to present an understanding of what knowledge is and how it is considered within literature relating to innovative business firms and strategic management.

Focus on knowledge invite for a coherent definition of the concept. However, there is an absence of a single agreed upon definition within academia. To ensure consistency within this study, a definition of knowledge provided by J. R. Howells (2002) is applied: *"a dynamic framework or structure from which information can be stored, processed, and understood"*. Despite the lack of a universal definition in business literature, many scholars acknowledge the division of knowledge into tacit and explicit knowledge (J. R. Howells, 2002; W.-H. Lai, 2013). Leonard and Sensiper (1998) explains knowledge as a spectrum where one extreme is tacit knowledge only existing within people's bodies and minds, while the other extreme represents explicit knowledge with information being codified, structured, and available to others. In this spectrum, most knowledge exists on the scale between the two extremes as a compound of tacit and explicit knowledge (J. R. Howells, 2002; Leonard & Sensiper, 1998).

Explicit knowledge is knowledge and know-how that is possible to codify or transmit in a systematic language while it does not require any direct experience to be understood. More specifically, explicit knowledge is the type of knowledge that can be found in manuals, patents, and blueprints (J. R. Howells, 2002). The critical distinction between explicit and tacit knowledge lies in their transferability. Explicit knowledge is easily transferred and could be regarded as a public good, possible to sell or give away without losing. Except the small fraction protected by copyright or patent laws, explicit knowledge is difficult to appropriate (Grant, 1996). In opposite to explicit knowledge, tacit knowledge cannot be codified as it requires direct experience. It consists of know-how that is accumulated through informal learning from behavior and procedures. Tacit knowledge is usually associated with unconscious learning and could be explained as scientific intuition (J. R. Howells, 2002). For example, an acrobat depends on physical skills such as reflexes, muscles, and coordination to perform developed over time through repetition. Another example is that of a software developer unconsciously accumulating experience and intuition over time. Tacit knowledge could be embodied in both physical and cognitive skills, and the common element in such knowledge is the knower's inability to describe it to others (Leonard & Sensiper, 1998). J. Howells (1996), presents an accepted definition of tacit knowledge where it can be explained as *"non-codified, embodied know-how that is acquired via the informal take-up of learned behavior and procedures"*.

In contrast to explicit knowledge, tacit knowledge differs in the way that it is difficult, or even impossible, to transfer directly between actors. Leonard and Sensiper (1998) claims that much knowledge remains tacit even if it is possible to make it explicit, as individuals are often not aware of the knowledge they inhabit. Furthermore, codifying tacit knowledge allows it to be transferred, which would enable a risk of losing competitive advantage if the knowledge would transpire to competitors. However, it is important to recognize the fact that a majority of a firm's knowledge stock is stored within individuals who are the carriers of all tacit-, as well as most explicit knowledge. Which further presents difficulties for firms to grasp the size of their internal knowledge base. Considering the innovative process as production, a fundamental assumption of the knowledge-based view is that knowledge is both the critical input as well as the output variable of such production and subsequently the source of new value (Grant, 1996).

2.4 Innovation and the role of patents

This research recognizes the importance of knowledge through literature's view of its close relation to innovation as a key resource or element in the innovative process (Burnett, 2012; Grant, 1996; Nonaka, Toyama, & Nagata, 2000). Creative exploitation of knowledge through innovation has been pointed out as a key characteristic of the modern knowledge economy and encompasses the whole range from creative ideas to commercialization (Burnett, 2012). The importance of innovation can be observed in the fact that one-third of sales can be traced down to products developed in the last five years, in many industries. As pressure from foreign competition increases, firms needs to introduce new products to stay relevant in their customer's eyes and to protect their margins. Two important mechanisms of staying relevant to customers are to be able to sell products at an attractive price, which could be achieved through innovating the production process, the other is to be able to offer a product that meets the customer's need in the best possible way (Schilling, 2005). Nonaka et al. (2000) argues that the combination of knowledge and skills makes a firm capable of innovating products, processes, and services or developing existing ones in an efficient and effective way.

With innovation being a quite abstract concept, it is difficult to point towards a specific definition. However, the innovation process could be described as the activities which operate in the lifespan of an idea, from that of its conceptualization to its market introduction. Initially, R&D activities contribute to exploring and applying technological solutions for realizing the idea into an invention. Succeeding these are other organizational activities, e.g. marketing or production, which contribute to the market introduction and the appropriation of the preceded invention. These succeeding activities are often tough to pinpoint as they can differ significantly between various projects. Furthermore, as the innovation process includes many different activities, R&D can not exclusively explain the totality of a firm's innovative strength. This suggests a difficulty in obtaining an optimal instrument that can sufficiently incorporate all parts of the innovation process when measuring the innovative capacity of a firm. Ernst (2001) presents patents as being a possible instrument for measuring the R&D output and further *"reflects the elements of technological progress that lead to economic growth"*. However, the author recognizes that *"not all inventions are patentable, not all patentable inventions are patented, and the economic significance of inventions varies enormously"* (Ernst, 2001). Figure 2.1 depicts the scope of patents and recognizes that there is a limited range of all inventions which using patents as an instrument for measuring innovation can encapsulate.

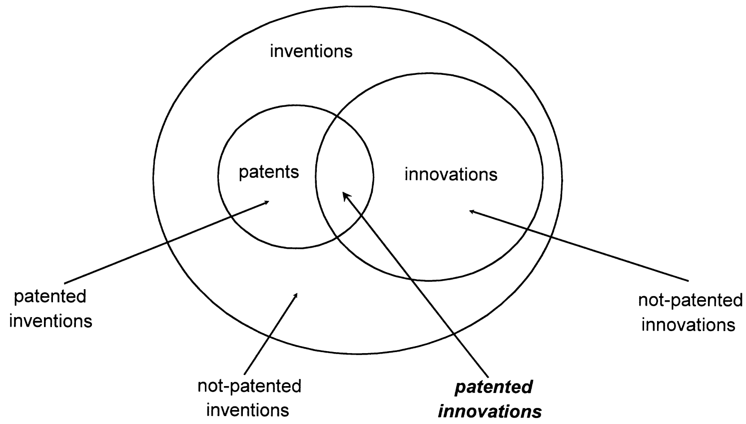

Figure 2.1: Relationship between patents, inventions, and innovation (Basberg, 1987)

Knowledge flows between organizations through different channels, such as technology transfer, investments, through research cooperation, or by professionals moving from one company to another. In contrast to tacit knowledge embedded within the individuals moving between companies, patents play the role as codified knowledge which introduces a reliable source to trace the movement of knowledge. The reliability of patents in combination with its bibliographic nature have made them a popular source of information for empirical studies of knowledge creation, innovation, and knowledge spillovers. For example, patent citation analysis is a broadly used method to examine the trajectory of technological development and has been used in several studies to map knowledge flows between regions, countries, and sectors (Hsu & Yuan, 2013). Hu (2008) uses patent statistics to examine knowledge flows and innovation in the context of the liquid crystal display industry in Taiwan. By back tracing patent citations, the author was able to identify the importance external knowledge from the US and Japan plays into equivalent Taiwanese latecomer industries (Hu, 2008). Aldieri and Vinci (2016), explains the patent citation method as following a paper trail of knowledge spillover, connecting the citing inventor to the cited inventor.

The use of patents as a performance measure has been a subject of long debate concerning patents' shortcomings. An important aspect of the criticism is the heterogeneity of patents, where a few very successful high-quality patents are given the same weight as the vast majority of low-quality patents making them very hard to compare accurately (Ernst, 2001; Hagedoorn & Cloodt, 2003). Also, a lot of the criticism concerns the comparison of different industrial sectors, large and small companies, and regional differences in patenting behavior (Hagedoorn & Cloodt, 2003). In some industries, patents provide good protection and stimulate firms to be more patent-active in contrast to industries where a patent only provides limited protection (Ernst, 2001). Furthermore, many scholars claim that the patent output only explains a small part of the R&D trajectory within a certain field, implying that a patent should rather be seen as an indicator of R&D performance instead of a measure (Ernst, 2001; Hagedoorn & Cloodt, 2003).

Despite the debate regarding the possible shortcomings of patents as an indicator of performance, there seems to be a consensus increasingly favoring its applicability in high-technological industries (Hagedoorn & Cloodt, 2003; Hu, 2008). Literature suggests that if patents are used to compare the performance of different companies, the results are more relevant when not comparing companies in different industries (Hagedoorn & Cloodt, 2003). Finally, it is imperative to consider a time-lag when measuring financial performance gained from patented inventions, as the innovation process includes several organizational steps preparing for market launch after a patent is granted to ensure appropriation of the invention (Ernst, 2001).

2.5 Firm performance

The shift from investments in tangible to intangible assets inherent in the change towards a knowledge-based economy has spawned the question of how a company should be valued rightfully. Decreasing investments in tangible assets such as physical goods, buildings, and machinery are in sharp contrast to increasing investments in intangible assets such as research and development, human resources, and marketing. The transformation of the global economy and the changing view of what constitutes a firm's most valuable asset has had implications in the relevance of traditional report systems. Financial reports and accounting systems have been too occupied with financial and physical assets while they have difficulties tracing and estimating intangible assets (Bornemann & Leitner, 2002).

Company valuation is a well researched but nevertheless difficult field. Examples, such as the burst of the dot-com bubble, illustrates this complex nature of estimating an accurate value of a company (Dowling, 2006). Several factors can affect the degree of difficultness in valuation. Dowling (2006), mentions new types of firms, in new industries, while DeCarolis and Deeds (1999) points to the complexity in the valuation of firms that does not have a product in the market and consequently no revenue. Different circumstances and company characteristics require different measurement methods for evaluating firm performance. Literature suggests different methods for measuring and comparing the performance between firms, usually divided into market-based methods and accounting-based methods (Erden, Klang, Sydler, & von Krogh, 2014).

In their article, DeCarolis and Deeds (1999) measures the performance of entrepreneurial firms in the biotechnology industry. The authors argue that it is problematic to use accounting-based methods to value those types of companies as they typically do not have a history of either revenue nor profit, which makes performance measures such as return on sales, profit margin, and sales growth, difficult to use and unsuitable for the case of comparison. These types of start-up firms are characterized by small tangible assets and large accounting losses, while their intangible assets, such as knowledge, represents the real value (DeCarolis & Deeds, 1999). Similarly, companies without revenue are unsuitable for the well-used performance indicator price-to-earnings ratio, commonly referred to as P/E ratio (Zheng, Liu, & George, 2010). P/E ratio could be defined as a performance indicator that is combining market-based and accounting-based measures (Erden, Klang, Sydler, & von Krogh, 2014). However, this measurement would be insufficient in an extensive study like this, including both companies with and without earnings. Companies without earnings would be given an undefined P/E ratio, making them impossible for cross-comparison and therefore introducing a risk to the reliability of the study (Erden, Klang, Sydler, & von Krogh, 2014).

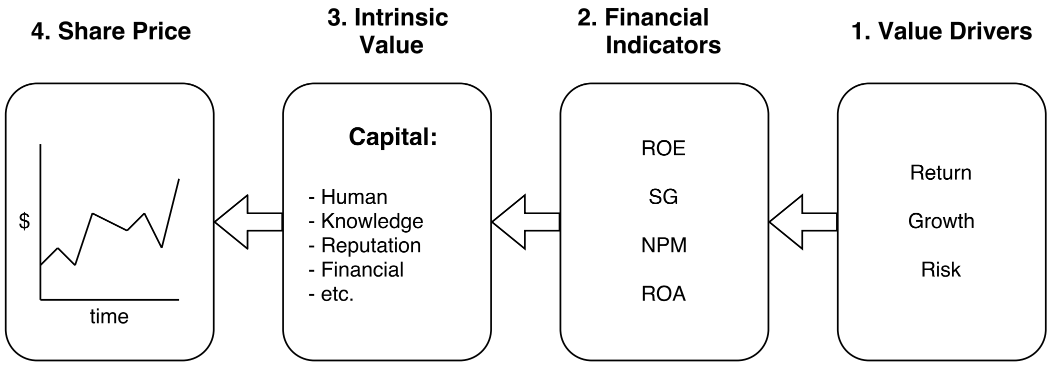

Figure 2.2: 4-part model based on Copeland et al. (2000)

The challenge of including all aspects of a firm, such as intangible and tangible assets, into the firm valuation process is evident. As presented earlier, there exist several theories regarding how to encompass a company's total value fully. However, one profound and widely used indicator is a firm's market capital, which has been used in economic theory to play the part of evaluating the firm value and thus firm performance (DeCarolis & Deeds, 1999; Dorestani, 2009; Dowling, 2006; R. Zhang & Rezaee, 2009). Copeland et al. (2000) presents a framework which argues for the usage of share price, and consequently market capital, as an indicator which incorporates the many aspects of a firm's valuable resources. Figure 2.2 presents the framework, titled the four-part model, which is a well-recognized general framework for company valuation (Dorestani, 2009; Dowling, 2006; R. Zhang & Rezaee, 2009). The framework is widely used to understand corporate valuation, both by companies and consultants, as well as business schools (Dowling, 2006; R. Zhang & Rezaee, 2009). The logic of the four-steps model provides a useful tool to understand how intangible assets, such as knowledge, impacts the value of a company.

The framework presents, as the name suggests, four stages of a firm's total value. The authors argue for how different stages of firm value are all subsequently captured by the fourth stage, namely the market price of a firm. Initially, the model presents how firm value is partly based on a firm's strategic outlook, in how return, risk, and growth are managed. The second stage presents a more fundamental view of firm value, where hard financial indicators are taken into account. Common financial indicators typically used in this process are net profit margin, return on equity (ROE), and sales growth (R. Zhang & Rezaee, 2009). This is usually the type of data used as input in the process when accounting-based methods are used to measure firm performance. However, a problem related to this type of indicators is that they are quite easy to manipulate, which can make them hard to correctly interpret (Dowling, 2006). Furthermore, looking solely on financial values can easily result in an unjust valuation of a firm's actual value. The total value of a firm rarely lies in the firm's tangible assets exclusively, but includes assets such as human capital, knowledge and other, more abstract, resources (Dorestani, 2009; R. Zhang & Rezaee, 2009). To include these aspects, the model presents a third stage which covers something referred to as the intrinsic value of a firm. Values shown at this stage is of particular interest for this study as it includes values from more abstract resources. Intrinsic value includes resources such as employees, trademarks, intellectual property, brand, and corporate reputation which has all increasingly become more importance in the "new economy" (Dowling, 2006). Literature in strategic management, employing the knowledge-based view, suggests that these types of resources are highly important as they differentiate companies and can contribute to achieving competitive advantage (Dorestani, 2009; Dowling, 2006; R. Zhang & Rezaee, 2009).

In line with the previous discussion about the intrinsic value and the increased recognition of intellectual property as an asset of rising importance, the importance of patents as a component of company value has also gained more attention. As an expression for this circumstance, a large number of researchers have acknowledged the need to develop a reliable model for assessing the value of patent portfolios. Patent portfolio assessment can provide valuable insights for objective comparisons of technological know-how between companies and consequently be a key to understand a firm's competitive position and prospects (Grimaldi, Cricelli, Di Giovanni, & Rogo, 2015).

Conclusively, the model suggests that the accumulated value included in each stage is captured when a company is priced on the stock market. Essentially, tangible and intangible assets are both incorporated into a firm's market price where resources such as patents, knowledge, and human capital are all included in the share price through the intrinsic value of a firm. This is in-line with the profound theory of market value namely the efficient market hypothesis presented by Fama (1970). According to the efficient market hypothesis, the market value of a firm captures all available information regarding the firm, including aspects such as the accumulated knowledge and its potential (DeCarolis & Deeds, 1999). In a perfect market, the share price will be at a level that catches all relevant information about the company. New information will be instantaneously, or quickly, reflected and eventually lead to a correction of the price (R. Zhang & Rezaee, 2009). In this case, the origin of new information can be from the company itself through e.g. reports or statements, but also from the outside, generally in the form of reports concerning competitors or prospects of the industry as a whole (Dowling, 2006). From this perspective, the short-term share price is mostly driven off the company's performance in relation to the expectations of analysts. However, the market also captures the long-term perspective of a company's prospects, which is visualized in the massive market capitalization of some internet companies that has still not made any profits (Dowling, 2006).

This study solely examines market-based indicators as measures of firm performance. Similar approaches to establish a fair evaluation of firm performance have been used by DeCarolis and Deeds (1999), who examined the relationship between firm performance, knowledge flows, and knowledge stocks in the biotech industry. Unlike Decarolis and Deeds who used market value on the first trading day after an initial public offering (IPO), Erden et al. (2014) used a longitudinal study to examine the link between knowledge flows and firm performance, also within the biopharmaceutical industry. Furthermore, Erden et al. (2014) argues that a longitudinal study looking at market value over time is a more accurate indicator of firm performance as the optimism amongst investors may result in a decreasing market value in the long-run after the IPO. Following this line of thought, this study uses a longitudinal approach to examine the firm performance through market value.

3

Theoretical Framework

The previous discussion regarding the intrinsic value and its importance as one of several components which add to the market value of a company points at an increasing recognition of intellectual assets as essential and valuable. Regarded as an intellectual asset, a firm's knowledge base is crucial as an enabler of value creation and innovation. Consequently, the firm's knowledge base should also relate to its market value (Dowling, 2006; R. Zhang & Rezaee, 2009). Employed individuals carry most of the knowledge constituting the knowledge base within a firm, and due to a high degree of tacitness, this asset is complex for competitors to imitate and is thereby considered an important source of sustainable competitive advantage (Campbell, Coff, & Kryscynski, 2012; J. R. Howells, 2002). However, the knowledge base itself is not enough to guarantee business success. An equally important aspect is the firm's ability to transform that knowledge into something novel and valuable. This process of exploiting the knowledge base could be seen as creating new knowledge out of already existing knowledge. Where the knowledge-based view considers this capability as the link between knowledge and competitive advantage (Grant, 1996; Woodman, Sawyer, & Griffin, 1993). Furthermore, appropriation refers to how much of the produced value that is captured by the company. Patents and the protection of intellectual property they provide has an essential role in enabling firms to reap returns from their innovative output (Grant, 2016).

3.1 Creativity, an enabler of innovation

Creativity and innovation are critical components in both growth and performance of organizations. Even if the term creativity is usually used to explain the creation of new ideas, it is not simply about the production of ideas (M. D. Mumford, 2012; Woodman, Sawyer, & Griffin, 1993). Creativity could rather be defined as *"the production of high quality, original and elegant solutions to problems"* (M. D. Mumford, 2012). In this way, creativity is a type of performance from groups or individuals, and ultimately a product of the human cognition. Compared to other cognitive activities such as recall and recognition, it should be considered as a demanding, high-level form of cognition.

A question of which problems, when solved, would benefit the most from creativity, emerge when it is considered as high-level cognition producing high quality, original, and elegant solutions to problems (M. D. Mumford, 2012). M. Mumford and Gustafson (2007) suggests an answer to this question, by stating that creativity is most beneficial if the nature of the problem to solve, is characterized by its complexity and novelty, but also if the problem is *"ill-defined"* in the way that it could be interpreted or solved in multiple ways. As a consequence, the production of new products, processes, and services, normally referred to as innovation, is only possible if preceded by creative problem solutions. Hence, creativity is a fundamental component, but not solely sufficient in constructing an organization's innovative capability (M. D. Mumford, 2012).

Organizational creativity is a concept exploring the creation of valuable new products, services, ideas, and processes. The innovative process is depending on a complex social system of individuals working together. Organizational creativity could be seen as a function explaining the creative output through the characteristics of organizational components and contextual influences, such as organizational culture, resource constraints, the outside environment, etc.. Extensive research has been targeting creativity of formal groups, or research teams, as it is a common way of organizing employees for research and development activities (Woodman, Sawyer, & Griffin, 1993).

A significant contribution from the organizational creativity theory is the linking of organizational creativity to individuals. Where theory suggest that organizational creativity is depending on group-, or team creativity, which in turn depends on the creative input delivered by the individuals involved. Figure 3.1 provides a simplified model of the complex multilevel interactions between different levels in an organization. The dotted lines in the figure represent feedback between organizational levels (Woodman, Sawyer, & Griffin, 1993). In this study the Interactionist Model of Organizational creativity is used to shed light on the individual aspects and how they are related, and to contribute to the overall creative output of a firm, framing the link between the patent output and its registered inventors (Woodman, Sawyer, & Griffin, 1993).

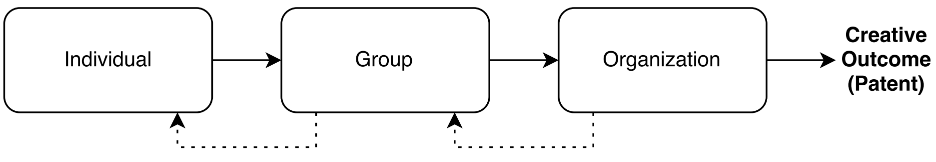

Figure 3.1: A simplification of the *Interactionist Model of Organizational Creativity* (Woodman, Sawyer, & Griffin, 1993)

Most recent research in organizational creativity is focused on teams and their role in the creative production. There exist several reasons for the increased interest in teams and the social context they provide, but some of the more important ones are increased global competition, increasingly advanced technology, and the knowledge-based economy. Today, organizations are facing increasingly complex challenges, which has made it unlikely that a single individual occupies all knowledge required to solve a problem. For this reason, teams have been considered the solution as they provide the benefit from combining several individuals complementary knowledge assets. Furthermore, additional benefits occur from diverse perspectives, diverse information, and the advantage of being able to capitalize on different sets of skills among the team members. The basic assumption of team superiority in creative work is that the team's creative production has the potential to exceed the sum of its members individual production.

3.2 Diversity and its linkage to innovation

Grant (1996), states that *"without benefits from specialization there is no need for organizations comprising multiple individuals"*. This premise is fundamental to all theories of the firm and has its roots in the assumption that there are gains to be made from specialization in the storage and the acquisition of knowledge. Furthermore, and even more important for this study, the assumption that a wide range of specialized knowledge is required for production (Grant, 1996).

Team composition is a well-recognized subject in research studying team performance concerning creativity and innovation. The field is broad and covers a whole range of subcategories such as demographics, skills and abilities, personality, education, knowledge, and other job-relevant variables (M. D. Mumford, 2012). Diversity is not a homogenous concept, and different types of diversity subcategories are present in an organization and affect it in different ways (Kristinsson, Candi, & Sæmundsson, 2016). Harrison and Klein (2007), states that the term diversity has been used differently since it is vague and could be defined in many ways. The authors make an attempt to explain the concept as *"the distribution of differences among the members of a unit with respect to a common attribute, X, such as tenure, ethnicity, conscientiousness, task attitude, or pay"* (Harrison & Klein, 2007). (M. D. Mumford, 2012), claims that in general terms, literature has explained diversity as the distribution or variance of characteristics within a team.

Many studies have come to the conclusion that there exist a positive correlation between a firm's innovative capability and the diversity in its knowledge base. Diverse knowledge bases provide a firm with higher absorptive capacity, making it better suited to exploit both external and internal knowledge by increasing interaction and learning (Cohen & Levinthal, 1990; Østergaard, Timmermans, & Kristinsson, 2011). Improvements in innovative capabilities are explained as a combined result of several benefits connected to employee diversity. Diversity in human resources brings variety in knowledge, skills, and experiences, claimed to make an organization more open towards new ideas, which boosts creativity. Furthermore, variation in age, gender, ethnicity, and background, should ideally increase the knowledge base as well as contribute to an environment with improved interaction between different knowledge disciplines. As diversity increases so do the possible combinations and applications of knowledge, which has a positive impact on a firm's innovative capabilities (Østergaard, Timmermans, & Kristinsson, 2011).

In early research on creativity and team composition, the general assumption was that diversity had a positive influence on the creative performance because of diverse experience and knowledge among team members (M. D. Mumford, 2012). Still today, diversity is thought of as something positive that has the potential to contribute to business success. *"Hire and train for diversity"* has been an increasingly popular topic in the business press, sending a clear message to managers to focus their recruitment on diversity aspects to achieve competitive advantage (Kristinsson, Candi, & Sæmundsson, 2016). Nonetheless, experts are calling for more discretion, arguing that diversity is not unconditionally superior to homogeneity under all conditions (Kristinsson, Candi, & Sæmundsson, 2016; M. D. Mumford, 2012; Østergaard, Timmermans, & Kristinsson, 2011).

The broad and sometimes unspecific use of the term diversity is also reflected in empirical studies of the subject (Harrison & Klein, 2007; M. D. Mumford, 2012). Differences in its definition have made empirical results regarding the organizational outcome of diversity too broad, different, and incomparable. Some scholars claim that diversity in demographic characteristics such as gender, age, and ethnicity are likely to bring conflicts to the team while informational diversity such as variance in industry experience, education, and functional background are expected to spur innovation (Harrison & Klein, 2007; Kristinsson, Candi, & Sæmundsson, 2016).

3.2.1 Diversity types

To bring structure and make the diversity concept more clear, many researchers have endorsed the division of the concept into three subcategories: demographic diversity, functional diversity, and psychological diversity. Despite that, the actual labeling of the categories sometimes differs between reports and researchers, in general, there seems to be a consensus about the content.

Demographic diversity concerns the most obvious variations in a team such as age, gender, and ethnicity. These characteristics are commonly used as proxies to explain deeper differences in experience and cognition (Kristinsson, Candi, & Sæmundsson, 2016). This category rests upon assumptions such as that an old African man will have other experiences and values compared to a young woman from South America, and therefore impact group performance in different ways.

Psychological diversity concerns a team's behavioral preferences. Diverse teams in behavioral characteristics might be better in complex problem-solving. However, a disadvantage sometimes put forward is the increased possibility for conflicts within the team. Even if the level of conflict could be expected to be mitigated over time, it can not be expected to disappear entirely. Differences in personalities are considered to be stable over time, but the drawback is the difficulty in measuring such variations in a reliable way (Kristinsson, Candi, & Sæmundsson, 2016).

Functional diversity or informational diversity refers to variations in functional background, industry experience, function in the organization, education, skills, and abilities - the dispersion of accumulated knowledge within different fields (Hülsheger, Anderson, & Salgado, 2009; Kristinsson, Candi, & Sæmundsson, 2016; M. D. Mumford, 2012). Models of team creativity indicate that functional diversity is the facilitator of creativity, and most studies, aimed to evaluate the correlation, have found positive results (Hülsheger, Anderson, & Salgado, 2009; M. D. Mumford, 2012). The creative benefits from functional diversity could be explained as a compound of several mechanisms interacting. High levels of functional diversity provide access to an extended pool of knowledge, industry experience, and expertise, but also improved networks and contacts (Kristinsson, Candi, & Sæmundsson, 2016; M. D. Mumford, 2012; Y. Zhang, 2016). An important aspect of contacts is that functionally diverse teams seem to trigger communication with the environment outside the team borders, providing access to several origins of information and perspectives for improved problem-solving (Hülsheger, Anderson, & Salgado, 2009; Y. Zhang, 2016). Furthermore, such teams could be considered as a combination of individuals with an improved representation of the environment, providing a greater richness in problem-solving perspectives, and therefore being more creative and innovative (Kristinsson, Candi, & Sæmundsson, 2016). Several studies examined the relationship between functional diversity and creativity and most of the results point in the direction of a positive correlation between the two. However, the problem is that researchers, in general, have designed their research to approach functional diversity as one lumped concept, and have left the nuanced effects introduced by functional diversity variables, such as education, job functions, industry experience, etc., on creativity relatively unexplored (M. D. Mumford, 2012). This study will focus on various aspects of functional diversity and seek to relate it to firm performance. When the term diversity is discussed from this point, and forward, it will refer to functional diversity alone and not taking any aspects of demographic or psychological diversity into consideration. The rationale being that the available quantitative data allows for only an analysis of functional diversity. Whereas psychological- and demographic diversity would require a different source of data and approach to be measured.

A firm's level of functional diversity can result from either the aggregate distribution of several specialists in different functional domains, or the existence of generalists with dispersed experience and functional background. By far the most used conceptualization of diversity in literature is the dominant function diversity of a group. The dominant function approach categorizes employees by the most representative aspects of their career and considers the degree to which group members differ in their dominant function (Bunderson & Sutcliffe, 2002; Yap, Chai, & Lemaire, 2005). Despite the general trend of more organizations using teams for development and complex problem solving, empirical research on team composition and creativity is limited and somewhat contradictory (M. D. Mumford, 2012). Hülsheger et al. (2009) provides an overview of the research field by examining relevant reports published over the last 30 years. Out of 15 studies, only eight were looking at the job-related background when examining team-level diversity and creativity. Harrison and Klein (2007), claims that the quality of diverse teams has been almost taken-for-granted in organizational literature, despite the fact that the concept is seldom explicitly defined in research. An extensive study of 1,648 Danish firms found significant support in line with previous studies when trying to link diversity to creativity, where the authors identified positive correlations between diversity in education, and a negative or neutral correlation between age, and innovation (Østergaard, Timmermans, & Kristinsson, 2011). Kristinsson et al. (2016) refers to a study examining team diversity in functional background and education level, concluding that they are positively related to innovation in the financial sector, in this case, measured as the number of new products, services, and computer software produced.

As briefly mentioned previously, diversity is not only existing between individuals in a group but could also be found within an individual, sometimes referred to as intrapersonal diversity. However, this study is using the term individual-level diversity when referring to the diversity of an individual's background. By examining an individual's background, this kind of intrapersonal diversity could be assessed through the examination of how many years of their career is spent in different functional positions. In this way, an individual can be placed on a diversity scale stretching from very narrow functional specialization to broad general experience from several functions (Bunderson & Sutcliffe, 2002; Yap, Chai, & Lemaire, 2005). While most literature discussing the subject of diversity is taking a team or group approach when examining the issue, only a few studies investigate individuals diversity in the same context. Yap et al. (2005) examined the diversity impact on innovative performance amongst the individuals' in management teams. The cross-sectional study was performed on fifty SMEs in Singapore and found a positive correlation between individuals' diversity and innovative performance. However, an important implication was that individual-level diversity turned out to be more beneficial in small growing firms while the positive effects faded out as the size of companies grew. A negative relationship was observed when functional diversity was examined at a group level (Yap, Chai, & Lemaire, 2005). Positive effects of intrapersonal diversity on performance was also found by Bunderson and Sutcliffe (2002) who found that intrapersonal diversity improved communication and information sharing. In an extensive study, Verhoeven (2015) examined 229 innovators that had won awards for significant new inventions. The author found a significant correlation between individuals' experience diversity and novelty in their innovative work, which led to the conclusion that knowledge in different technological domains can be leveraged to increase novel inventive performance. Furthermore, the author provides two mechanisms through which novel inventions spawns: 1) through truly new idea generation or 2) through the recombination of inventions out of old ones, where both showed to increase in relation to the individual's experience diversity. Moreover, the article contributes to the understanding of increased novelness by putting it in relation to path-dependency, a concept assuming the direction of old research to define the trajectory of future research. The diverse functional background provides new knowledge, experiences, and approaches, facilitating the generation of new and novel idéas from the respect that it is outside the path-dependent avenue of technological development (Verhoeven, 2015). Similar observations were made by Olson, Walker Jr, and Ruekert (1995), who by examining cross-functional teams (diverse on a group level), concluded that the positive effect of diversity depends on the level of newness in the innovation project. Their observations show that diversity indeed has a positive effect on truly new innovations while it is less beneficial in incremental innovation (Olson, Walker Jr, & Ruekert, 1995).

Despite the general positive assumption of diversity in innovation management literature, there exist findings which counter that view (Lettl, Rost, & Von Wartburg, 2009). Grant (2016) implies that the benefits of diversity could have limitations by stating that the creation of new knowledge requires individuals to be experts in a particular knowledge field. The author argues that this requirement is a consequence of the principle of bounded rationality, a theory favoring specializations due to limitations of the human cognition regarding the acquiring, storing and processing of knowledge (Simon, 1955). However, Grant (2016) is not making any further attempts to explain or define the meaning of the word expert in his work. If the word regards the time, an individual has spent in a particular field, or just if that field is considered their dominant function. Further understanding of the mechanisms behind possible limitations of diversity is provided by Lettl et al. (2009). The authors compare independent inventors of medical equipment technology with corporate inventors, where they found no positive effect of increased diversity when performance was measured as the number of future patent citations. More surprisingly, when examining the performance of independent investors alone, those individuals turned out to decrease their performance as a function of increased diversity. Furthermore, the authors refer to an ongoing discussion regarding becoming too diversified. In line with the principle of bounded rationality, they suggest that there is a restriction in the amount of diverse information an individual can process and combine in a meaningful way (Simon, 1955). Too much diversity has been found to result in information overload which can have a negative effect on performance. By providing too many contradicting perspectives, high levels of diversity can make it difficult to sort out the best solutions. Also, this results in too much complexity in resolving and defining problems, which can make diversity cause failure (Lettl, Rost, & Von Wartburg, 2009).

3.2.2 Hypotheses

When measured by market capitalization, a firm's performance presents an aggregated view of all assets known to the market, tangible as well as intangible (DeCarolis & Deeds, 1999; Fama, 1970). As part of those assets, the intrinsic value presented in the four-stage-model captures intangible assets such as intellectual property and human resources (Dorestani, 2009; Dowling, 2006; R. Zhang & Rezaee, 2009). This study argues that functional diversity should indeed be traceable all the way to a firm's market capitalization as it is pointed out as an enabler of creativity and innovation (Hülsheger, Anderson, & Salgado, 2009; M. D. Mumford, 2012; Østergaard, Timmermans, & Kristinsson, 2011), and critical to the growth and performance of firms (M. D. Mumford, 2012; Woodman, Sawyer, & Griffin, 1993).

The use of functionally diverse teams in R&D and innovative work is an established strategy to boost creativity, which also has support in research (Hülsheger, Anderson, & Salgado, 2009; M. D. Mumford, 2012). While theory regarding diversity is almost exclusively approaching the concept as the interaction between team members and taking a dominant function approach, more fine-grained research considering background diversity on an individual level is rare (Verhoeven, 2015). Verhoeven (2015) carried out a large study presenting positive correlation between functional diversity and innovative performance, however, limited to only examining highly novel inventions. Similar results, however on a higher hierarchic level, is reported by (Yap, Chai, & Lemaire, 2005) who confirmed the positive correlation between individuals' diversity and innovative performance in the context of management teams. Contradictory to the findings of previous literature are claims from authors such as Grant (2016) and Simon (1955), calling for higher levels of individual specialization rather than diversity to solve increasingly complex tasks and findings pointing at negative effects of individual functional diversity in narrow contexts (Lazear, 2004; Lettl, Rost, & Von Wartburg, 2009). However, the stance of this study is that functional should have a positive effect on firm performance. The rationale is built on the consolidated understanding of both group-level and individual-level literature which has previously identified benefits from having a higher degree of diversity within and between individuals and team members (Bunderson & Sutcliffe, 2002; Hülsheger, Anderson, & Salgado, 2009; Kristinsson, Candi, & Sæmundsson, 2016; Olson, Walker Jr, & Ruekert, 1995; Østergaard, Timmermans, & Kristinsson, 2011; Verhoeven, 2015). In this study, an attempt is made to examine some aspects of functional diversity done through the measurement of three specific variables in the job-related background of inventors. The variables are namely: 1) the dispersion of unique companies the inventor has been patent-active in, 2) the dispersion of industries the inventor has been patent-active in, and 3) the dispersion of technological patent classifications the inventor has been patent-active in. Consequently, we propose the following hypothesis to be answered:

H_1 *A higher level of individual-level company diversity has a positive impact on innovation and thereby on firm performance.*

H_2 *A higher level of individual-level industry diversity has a positive impact on innovation and thereby on firm performance.*

H_3 *A higher level of individual-level technological diversity has a positive impact on innovation and thereby on firm performance.*

3.3 Experience, practice makes perfect

A logical assumption can be drawn in that individuals who have accrued a larger amount of experience will, in the future, have a higher efficiency when involved in production processes. However, it is necessary to understand how the experience differs between knowledge-intensive industries and manufacturing. Knowledge-intensive industries often require individuals to produce diverse output where the product often differs for each new iteration, such as patent production. In contrast, manufacturing is more monotone in its nature and might have a greater gain from learning effects as the individuals can spend more time learning the same thing and perfect it over time. Literature within learning by doing presents theory and evidence of a learning curve being present within manufacturing in the 19th and 20th century (David, 1973; Wright, 1936). Wright (1936) first presented the learning curve phenomena within the airplane manufacturing industry. The author observed that labor costs were reduced over time as an effect of learning, thus increasing production efficiency. Further evidence was found when observing the production costs within a steelwork facility in Horndal, Sweden. Although no further investments were made in the facility, the output rate in relation to man hours put in increased annually by approximately 2% (David, 1973).

These findings argue for an expansive application of the learning curve phenomena upon other fields of research, with an assumption that the process of learning increases an individual's experience and thus positively affects their efficiency. Levinthal and March (1981) strengthens this assumption when exploring learning effects among individuals within a technological domain. The authors find that the likelihood of errors and false starts is reduced when performing a task repetitively. This suggests that wherever there exist repetitive tasks, learning effects occur. Jain (2013) presents a quantitative study which seeks to identify the presence of the learning curve phenomena within research and development and innovation production. A domain relevant to that of this study, where the common denominator between this research and the one presented by Jain (2013) focuses on the characteristics of individuals within the patent production domain, namely inventors. By measuring the time behavior of patent production when shifting into a new technological domain, the author sought to provide evidence for the presence of learning effects among patent inventors. Subsequently, the research confirmed the existence of a learning curve for innovation/knowledge intensive industries. This brings a consensus in that production, whether knowledge intensive or other, is impacted by how much task experience an individual have accumulated previously. With literature indicating that an individual with a higher level of experience provides a more efficient and refined output when compared to the alternative.

Although with a clear, and reasonable, impact on output efficiency, the literature mentioned above has not discussed how the experience of inventors impacts inventive quality. Conti, Gambardella, and Mariani (2013) presents a study which sought to answer whether greater invention experience leads to an increased rate of breakthrough inventions. By looking at patent data, the authors could identify that inventors with a larger stock of previous inventions have a higher rate of generating breakthrough inventions when compared to brand-new inventors. This suggests that experienced inventors have a higher inclination of producing higher quality patents which would lead to breakthrough inventions. Depending on the owning entity's ability to appropriate the value from these breakthrough inventions, it is of interest to understand how firm performance is affected by employing inventors with a higher level of patent experience. Hall, Jaffe, and Trajtenberg (2005) presents a study which aimed at analyzing what effect patent quality, namely patent citation, have on the market value of firms. The authors identified that an increase in patent citations have a positive effect on a firm's market value. Which argues for a further interesting point to observe, namely the effect introduced by the quality of the particular experience an individual possess. Arguably, an inventor which have previously been involved in producing high-quality patents would have a greater understanding of how to further produce quality patents. This, in turn, would benefit the owning company, and the firm performance would benefit from employing inventors with higher levels of experience quality. With the previous research pointing towards a positive stance towards experience, hypotheses are constructed to test the effects of individuals' experience on firm performance.

H_4 *A higher level of individual-level patent experience has a positive impact on innovation and thereby on firm performance.*

H_5 *A higher level of individual-level patent experience quality has a positive impact on innovation and thereby on firm performance.*

4

Methodology

This section seeks to explain the methodology applied for this study. Furthermore, this section will attempt to unambiguously explain the stepwise process taken for the collection, processing, and analysis of the data applied for reaching a conclusion and for answering the hypotheses and subsequently the research question. The research was initiated with a feasibility study, which aimed at building an understanding of the data, and its applicability, i.e., how the data can be examined. This was done as the analysis and method is highly dependent on the availability of data.

4.1 Research strategy

Aforementioned, firm performance is a variable often measured through quantitative methods. The value of a firm is set by its overall financial value at a particular point in time. In contrast, knowledge variables are often descendants from soft qualitative values embodied within individuals. However, for this particular study, knowledge variables have been found through quantitative proxies, namely patents. Jointly, these two aspects guide this research towards a quantitative approach in order to reach a conclusion. More specifically, this research will face the research question by approaching the methodological field of econometrics. The methodological approach to scientific research taken within the field of econometrics is often referred to as logical positivism (Hoover, 2006). Positivism requires research to consistently follow the scientific method by approaching theory – or generating theory – in a fashion which allows for testing and validating the findings, i.e., there exists a preconception that the reality is found within the observations (Bryman & Bell, 2015). As previous statement suggests, the positivistic stance allows for both inductive and deductive research strategies, however puts constraints in how these strategies are implemented. More specifically, scientific knowledge originates from either *"... a deductive inference from indisputable axioms [or] an inductive inference from empirical data"* (Hoover, 2006).

A positivistic inductive research strategy refers to the construction of a theory from empirical observations, i.e., a theory is generated from the analysis of empirical findings. In contrast, a positivistic deductive research strategy aims to challenge theory through the collection, and analysis, of empirical data; i.e. hypotheses are constructed based on existing theory within a research field, and further tested by collecting and analysing data to verify or dismiss the theories these hypotheses are aimed at challenging (Hoover, 2006). This research applies the later of these two strategies, namely a positivistic deductive research strategy.

Initially, theory is examined and interpreted within the field of knowledge and innovation to understand the theoretical stances existing amongst authors in the field. This examination of literature is mainly aimed at finding a research gap inline with the interest and scope of this research. Once a research gap has been identified, a suitable research question was constructed in order to fill the existing gap. Secondly, the examination intended to build a greater understanding of the existing theories in order to allow for the construction of consistent and relevant hypotheses. Collectively these hypotheses are set to allow for a quantitative approach in answering the research question. Econometrics is often defined as a construct of the triangle between theory, mathematics, and statistics. Frisch (1933) defined econometrics as the *"[...] unification of the theoretical-quantitative and the empirical-quantitative approach to economic problems"*. Thus arguing for the application of hypotheses in answering the research question where quantitative statistical methods are designed to answer concrete hypotheses rather than an abstract research question.

More specifically a regression model is built to enable the quantitative analysis applied for answering the hypotheses and the research question. The regression model is based on the variables presented in each of the hypothesis, and a detailed discussion regarding the variables included is presented in section 4.4.

4.2 Constructing the theoretical framework

The construction of the theoretical framework for this study started from a couple of articles calling for more individual level research in the subject of knowledge creation. From these articles, a number of initial keywords were selected as input for the pilot study aimed to provide a rough understanding of the research field and to identify research gaps suitable for further examination.

This study has applied a systematic literature review to construct an understanding of the literature regarding the research subject. According to Bryman and Bell (2015), this is a preferred approach as it reduces researcher bias, as well as providing coverage of the literature. This research performed the systematic literature review using the following databases: Scopus, Google Scholar and the search engine provided by the library of Gothenburg University. In the process following the initial pilot study, new and more precise keywords were selected for the SLR pre-

Initial Keywords

Diversity	Experience
diversity innovation performance	*market value and patent quality*
individual diversity innovation invention	*patent learning curve*
group diversity innovation	*innovative capability*
individual functional diversity	*patent experience*
intrapersonal diversity	*experience quality*
diversity creativity innovation	*productivity*
team innovation performance	
individual background diversity	
individual informational diversity	
interpersonal diversity	

Table 4.1: Keywords identified in pilot study

sented in table 4.1. Articles generated through the SLR were carefully evaluated to fit the scope of this study, excluded irrelevant literature and including relevant ones. The inclusion of new keywords discovered in the evaluation process allowed for refining the search strings. The assessment process involved determining the literature's relevance using the inclusion and exclusion criteria, and also through a thorough evaluation of their abstract, repeating the process until a satisfactory level of saturation was achieved. A sign of saturation was an increasing level of cross-references that occurred in the later stages of the evaluation process. Articles that passed through the evaluation as mentioned earlier were read and rated by their relevance to the study and their amount of citations. The final set of literature was carefully studied, and relevant parts were used to construct the theoretical framework. The framework includes only articles published in scientific journals, which reduces uncertainties regarding the quality of the literature. This study makes no claim to cover all existing relevant literature, it has rather sought to identify key literature, concepts, and inconsistencies - seeking to *"know what is known"* which is argued by Bryman and Bell (2015) as one of the most important aspects of a literature review. Furthermore, adopting the procedure throughout the review process is claimed to reduce the risk of emerging bias, which is the rationale for using the inclusion and exclusion criteria presented in the following section (Bryman & Bell, 2015).

4.2.1 Inclusion and exclusion criterias

As this study aims to understand how individual level variables of diversity and experience, through the inventive output, affects firm performance, books and articles had to meet the following criterias to be included.

Inclusion: *functional diversity in teams and groups*; *individual or intrapersonal functional diversity*; *creativity drivers*; *knowledge creation and innovation*; *team performance in innovation*; *functional diversity and patent performance*; *experience-based learning*; *organizational memory.*

Exclusion: *psychological diversity*; *demographic diversity*; *diversity on higher organizational levels above team/group*; *functional diversity in contexts other than innovation, innovation and creativity.*

4.2.2 Backwards Snowballing Process

Backwards Snowballing refers to the process of analyzing the references of relevant literature included through the SLR process (Sayers, 2007). After the initial literature review, and in parallel with the SLR, additional articles were found in the references of the identified literature. New keywords such as *dominant function diversity* and *intrapersonal diversity* were found throughout the work and used in a refined search process to cover more related theory. This evolving process of tracing citations from relevant articles help to reduce the risk of missing relevant clusters of research due to a different usage of terminology. It was very apparent that various authors use different words to describe the same concept, e.g. *individual*, *intrapersonal*, *individual level diversity.* An obvious disadvantage of using this method is that it will always provide older articles. However, this risk was assessed to be counteracted by the usage of an SLR as a primary process.

4.3 Data sources

A number of different data sources have been employed to allow this research to answer the research question and hypotheses. Each data source serves a specific role in constructing a complete dataset which includes the required dependent and independent variables. There exists three separate datasets which are applied in the final scoring process; firstly an inventor dataset, secondly a patent owner dataset, and finally a dataset including patent owner performance.

4.3.1 Inventor dataset

The primary data source is a database provided by the Harvard Institute for Quantitative Social Science. R. Lai, D'Amour, Yu, Sun, and Fleming (2015) presents a study which aimed at disambiguating U.S. patent records. The authors have developed disambiguation algorithms used for differentiating unique inventors registered for patent records. The U.S. Patent Office (USPTO (2017)) database contains a vast amount of patent information as well as information for the inventors of these patents. However, the database does not provide any unique identifiers for determining two separate patent inventors which have the same first name, middle name, and surname. The algorithms provided by R. Lai et al. (2015) have enabled a method for producing such unique identifiers, which are missing from the native USPTO (2017) database, to patent inventors. These identifiers in turn allow researchers to ensure that two inventors sharing the same information, such as name and country, are in fact two separately unique inventors. The authors have further provided the processed dataset of the disambiguated patent information containing the result of executing the algorithms. The algorithm was executed on patent data from the USPTO (2017) with patents from 1975-2013 which is the final dataset included in this study. In total, this dataset includes 4,763,243 unique patents connected to 3,421,276 unique inventors. Each patent have on average 2,25 inventors registered to it.

4.3.2 Patent owner dataset

The previously described dataset allows solely for the processing of individual inventors and their characteristics. However, it does not provide any information regarding the companies owning each patent and thus employing the associated inventors. It is essential to correctly link each patent to a specific company as this study seeks to discover how the performance of each company is impacted by the individual inventor's experience and diversity characteristics. To enable such linkage, ORBIS (2017) provides a unique identifier including firm specific variables of the owning company for each patent in the USPTO (2017). Thus, a dataset of all patent data from the USPTO (2017) between 1975-2013 was extracted from ORBIS (2017) and linked to each patent in the primary disambiguous dataset provided by R. Lai et al. (2015). The linking process will be further discussed in section 4.7. The purpose is to ensure that each patent and inventor has an identifiable owner company.

The purpose of the company dataset is to ensure that patent inventors are connected to an owning company at a certain point in time. Section 4.7 presents further explanation of the linkages made between the two datasets. This dataset includes all patents registered in the USPTO (2017) between 1975-2013 available in the ORBIS (2017) database. Resulting in 8,028,400 patents in total. Evidently that not all these patents are used for the final data integration as not all of these are included in the disambiguated inventor dataset previously presented.

4.3.3 Patent owner performance dataset

Finally, a dataset with granular company information was integrated. The dataset include company information covering performance indicators and control variables used for the final regression model made available through ORBIS (2017). Mainly, the aim of the performance dataset is to build the panel data required to execute the regression tests on. The dependent variable, market capital, is integrated through the inclusion of this dataset. Furthermore, this is also the dataset the introduces a lot of constraints to the breadth of the study. The previously presented datasets generates a collection of companies linked to patents, however to all of these companies are possible to evaluate. The reason being that many are not publicly listed or does not have sufficient market data available. Nonetheless, this dataset results in a collection of 10,860 publicly listed companies worldwide. Another important point to take into consideration is the fact that not all publicly listed companies own patents. This further constrains the breadth of the study.

4.4 Model variables

This section presents the variables incorporated into the regression models executed to answer the research question. To increase the model fit, a number of control variables were included argued by the complexity of all the forces in play affecting a firm's market performance.

4.4.1 Dependent variable

This study aims at understanding how firm performance is impacted by different diversity and experience characteristics amongst the inventors employed. Thus putting firm performance as the dependent variable in the model. Section 2.5 presents a thorough presentation of how literature regards firm performance in quantitative economic research. Several measures were presented whilst only one was suitable for this particular study, namely market capitalization. Copeland et al. (2000) presented the four-step model which demonstrate how market capital incorporates multiple aspects of a firm's full value. The model suggests that both tangible and intangible assets are valued into the market price. This suggests a suitable approach for measuring the impact of an intangible asset such as knowledge, as in the case of this study. The third step of the model presented by Copeland et al. (2000) titled intrinsic value, refers to abstract values such as reputation capital, human capital, knowledge capital, etc. This step argues for the relevance of applying market capitalization as a measure for firm performance. Market capitalization is measured annually for each firm, at the firm's account date. This is made at a particular point in time each year. That point in time differs for each company depending on the end of a firm's fiscal year, e.g. Apple Inc. past three account dates were 24/09/2016, 26/09/2015, 27/09/2014. This is the case for all companies included in the final dataset.

Section 4.3 provides an extended explanation of the data sources used for incorporating the market capitalization of firms.

4.5 Independent variables

The independent variables are set to cover the constructed hypotheses. They aim to test the hypotheses by being tested against the dependent variable. As the study aims at measuring individual-level knowledge factors it is imperative to ensure that the variables applied are indeed measured on the individuals inhabiting a firm, and no other organizational level.. Subsequently the independent variables are firm centered. However, the values are all descendants of the individuals employed by the company during a particular year. It is important to note that the inventors who are referred to in this study, are inventors who have been involved in granted patents registered to a company during the patent application year. The rationale for using such data is found in the lack of other available data. Due to the limitation of public information, it is not possible to look into each inventor within a firm, and thus patents are used as a proxy of knowledge amongst inventors in the same manner as previous research (Aldieri & Vinci, 2016; Hsu & Yuan, 2013; Hu, 2008). A firm has a number of inventors employed during a particular year, and each of these inventors has a score based on their patent engagement previous to a particular year. Patent engagement entails a patent application activity. Thus, it is essential to recognize that these inventors do not represent the complete inventor base employed in a company.

4.5.1 Company diversity

Previous research have discussed the notion of functional diversity, which relates to individuals' previous experience in terms of their exposure to certain functional areas and previous company experiences (Kristinsson, Candi, & Sæmundsson, 2016). Company diversity refers to individuals' company experience. It is a sum of each inventor's in unique company C experience previous to year T. Equation 4.1 presents how company diversity is accumulated within a company at time T.

$$company\ diversity(T) = \sum_{i}^{n} \sum_{t}^{T} C_{it} \tag{4.1}$$

4.5.2 Industry diversity

Industry is a variable measured by looking at companies' NACEv2 code. The NACEv2 is a standardized classification system which allows for observing technological involvement of firms on different levels of granularity. Table 4.2 presents four levels of NACEv2 categories. There is a palpable difference in the required knowledge between categories 25 and 26 at level 2 while arguably no significant difference between the categories at level 3 or 4. Schnabl and Zenker (2013) provide an understanding in that the difference between knowledge intensive industries and less knowledge intensive industries is made on the second level of granularity. This study looks at the second level of granularity in terms of industry diversity, i.e., industry diversity is measured when a larger technological difference is present. This level is chosen as a small difference in industry diversity does not necessarily provide an individual with a lot of new industry specific knowledge. Whereas, a larger difference may.

Level	Category	Title
1	C	*Manufacturing*
2	25	*Manufacture of fabricated metal products, except machinery and equipment*
2	26	*Manufacture of computer, electronic and optical products*
3	262	*Manufacture of computers and peripheral equipment*
3	261	*Manufacture of electronic components and boards*
4	2611	*Manufacture of electronic components*
4	2612	*Manufacture of loaded electronic boards*

Table 4.2: NACEv2 Levels

Industry diversity is measured similarly as the previous diversity variables. It is a sum of the inventors' n, unique industry I experience previous to time T. Equation 4.2 presents the equation used for aggregating industry diversity from employees.

$$industry\ diversity(T) = \sum_{i}^{n} \sum_{t}^{T} I_{it} \tag{4.2}$$

4.5.3 Technological diversity

Technological diversity refers to the amount of different technological fields, defined by patent's technological inherence at four different levels of granularity. These levels are; section, class, subclass, and group. Initially, in 1968 the IPC consisted of 8 sections, 639 patent classifications, inventors have worked within previous to year T. Patent classifications are constructed by a standardized code system, namely International Patent Classification (IPC). Previous research has implemented the IPC system on the four-digit sub-class level for measuring technological diversity (Huang & Chen, 2010). Literature suggests that the IPC system allows for a good proxy of technology breadth (e.g. Miller (2004)). This study has also chosen to measure technological diversity through patents' subclass level. Equation 4.3 presents how technological diversity is accumulated in a company at year T. It is a sum of each inventor's in unique patent classification PC experience previous to year T.

$$technological\ diversity(T) = \sum_{i}^{n} \sum_{t}^{T} PC_{it} \tag{4.3}$$

4.5.4 Experience

Learning curve effects have been a subject of interest for many year. As discussed in section 4.5.4, learning curve effects suggests a positive impact on the efficiency and quality of the production output. Jain (2013) performed a study which discovered a positive effect on efficiency of innovation output amongst innovators based on the amount of previous involvement in patent production. Previous research have applied patent count as a measure for patent experience which suggest the same application in the case of this study (Conti, Gambardella, & Mariani, 2013; Jain, 2013). The experience is measured by the sum of patents P each inventor's in have been involved with previous to year T. Equation 4.4 displays how experience is gathered annually in a firm where in are all the inventors which have been involved in a patent application P at year T.

$$experience(T) = \sum_{i}^{n} \sum_{t}^{T} P_{it} \tag{4.4}$$

4.5.5 Experience quality

Inventors with a higher patent quality is arguably more intellectually valuable in comparison to those with lower (Conti, Gambardella, & Mariani, 2013). Literature presents a method for identifying star scientists through observing article citations. Rothaermel and Hess (2007) identify star scientists by observing the number of articles citing a particular article, and putting it in relation to the technological field which the article is relevant in. An article is identified as a star article if the number of citations is found to be three times the standard deviation from the mean citing articles for the technological field at a specific year. The year aspect becomes relevant as a younger article has not had as many years to accumulate citations as an older article. Thus, a younger article must solely compete with the yearly mean at which the article was published within its technological field. Another aspect included by having a yearly moving average is technological relevance. A technological field might not accrue as many citations as it previously did, thus decreasing the amount of citations within that particular field. Hall et al. (2005) presents a study which identified a positive correlation between patent citations and market value of the firm owning the patent. This further argues for the observation on patent citation as a metric for measuring experience quality. The same process was applied to this study. A star patent is identified if the number of citations surpass three times standard deviation of the moving average citation count at its publication year within the patent classification in which the patent is registered. Equation 4.5 presents how experience quality is gathered in a company by summing the number of star patents SP each inventor $i \rightarrow n$ have been registered to previous to year T.

$$experience\ quality(T) = \sum_{i}^{n} \sum_{t}^{T} SP_{it} \tag{4.5}$$

4.6 Control variables

As the dependent variable market capitalization is highly erratic, it is difficult to fully encapsulate all variables which may impact its value. There might be fluctuations in the particular industry the firm operates in, broad market fluctuation a particular year, or other exogenous events impacting the firm's value. A number of control variables are included to increase the model fit and to ensure that the effects generated by the independent variables are more accurate. The following control variables were chosen by their use in previous literature which discuss their impact on firm performance, and their availability in the data sources.

4.6.1 Non-financial variables

Market age

Previous literature argues that the number of years since listing is the most meaningful metric of firm age (Shumway, 2001). Initially, firm's are often highly volatile due to the amount of uncertainties present when introduced to the public market. Giving a firm more time on the market will smoothen out these volatilities. Fama (1970) presented the efficient market hypothesis which argues that the market values a firm perfectly in accordance to the information available. This suggests that a firm's market value will be less volatile the more information available to the public. Pástor and Pietro (2003) argues that uncertainties regarding a firm's future profitability decrease over time. As such, the longer a firm have been on the market, the more information have been incorporated into the firm's share price and thus making it less volatile over time. For these reasons it is of interest to include a firm's market age into the final models to filter out for such effects. The market age is added as a control variable based on the amount of years since a firm's IPO year.

Company patents

A company's patent portfolio holds arguably a substantial amount of its competitive possibilities and may therefore have an effect on the company's market value (Ernst, 2003). The amount of company patents are incorporated into the models as a control variable to filter for such effects. It is an annual value, based on the amount of patent applications made at a particular year. This value follow the moving aggregated counting explained in section 4.7.4, where all scores are presumed to have an impact on the company for a five years period. All included patent applications are patents which will at a later stage be granted. It further hints for a firm's innovative output.

Company star patents

Due to the significant importance of high quality patents presented by Hall et al. (2005). It is of interest to filter out for such effects in the final model. Thus, a control variable with the counted star patents of each company per year is included. This is also a value counted with a moving aggregated score count. The rationale for including this control variable is that experience quality is calculated on the quality of the patents an individual have been involved with. To ensure that this is not the firm's patent quality, this variable is included for accounting firm-level effects.

Year

The final dataset is formed as panel data with yearly measures. This includes market capitalization on an annual basis. As a firm's market capital may fluctuate over time due to exogenous forces, the year is factored into the model which allows accounting for such fluctuations and filter these out from the independent variables. Fluctuations such as business cycles and market crashes may impact the market value of a firm which are taken into account by incorporating year as a control variable.

Industry

While patent provides good protection in some industries, they provide poor protection in others, this affects the appropriability and willingness to file patent applications (Hagedoorn & Cloodt, 2003; Hu, 2008). Literature suggests that the use of patents as a performance indicator is difficult in studies comparing companies in different industries (Hagedoorn & Cloodt, 2003). Using a dummy variable to eliminate the industry specific impact on the outcome aims to adjust for performance variations created to differences in patent protection and other industry specific fluctuations in market capitalization amongst the companies observed.

4.6.2 Financial variables

Accounting based measures are often used when setting firm share prices. As argued previously in section 2.5, such measures do not cover the full value of a firm, however they do account for a significant amount. Thus making it of interest to incorporate various accounting based measures to filter out any noise in the final models and hence getting a more accurate read on the results. The included accounting based variables are derived from the ORBIS (2017) database which provide accounting data converted into $US for all firms. The values are based on the official reports given at the firm's account date.

Operating revenue

Chandra and Ro (2008) argues for the importance of revenue when predicting the market value of a firm. Revenue accounts for all incoming capital of a firm, and thus making it inherently important when estimating its market value. This argues for why a large portion of a firm's market capital should be affected by its operating income. For these reasons, the annual operating revenue have been incorporated as a control variable into a portion of the final models. This is further used as a measure of firm size in many countries (Eurostat, n.d.). Erden et al. (2014) account for the market impact made by the size of a firm.

EBITDA

Another financial measure which allows for an obstructed view of firm performance is earnings before interest, taxes, depreciation, and amortization. This measure is a profitability indicator which indicates a firm's operational cash flow (tagkey2001i, 2001). A firm's profitability indicates how efficiently it handles its operating revenue. Thus it is of interest to incorporate this as a control variable to filter out any noise generated by such measures. An annual EBITDA value is incorporated in the models.

Number of employees

The annual number of employees are included as a control variable to avoid possible impact on performance that is only a function of personnel input. Furthermore, adjusting for this variable also serves the purpose of including some aspects of company size into the model. Erden et al. (2014) recognize the market value impact introduced by the size of a firm.

Research and development

In line with previous variables targeted to adjust for some of the concrete accounting based figures, one R&D parameter have been included as a control variable. This parameter is namely R&D Expenditure. R&D expenditure can be assumed to correlate a firm's market performance as it part takes as an accepted measure for a firm's innovative input (Burgelman, Maidique, & Wheelwright, 1996; Cohen & Levinthal, 1990).

Total assets

This measures refers to the total value of a firm's tangible assets. This measures all current assets and fixed assets. This is a highly concrete indicator of how much known value a firm is possess. This measures is incorporated as a control variable to filter out any noise generated by the impact it may have on the dependent variable. Erden et al. (2014) includes Total Assets as a control variable to account for firm size effects on a firm's market value.

	Disambiguated Patent Dataset	ORBIS Patent Dataset
Patent ID	6185789	US6185789(B1)
Owning Company		US120449744L
Patent Citing		17
Patent Class		D01G15/24
Inventor Firstname	JOHN D	John D.
Inventor Lastname	HOLLINGSWORTH	Hollingsworth
Inventor Country	US	US
Publication Date	2001	2001-02-13
AppDate	05/04/1999	
Unique Inventor ID	03858276-1	

Table 4.3: Patent Samples

4.7 Data processing

This section will present the steps taken to process the data sources and subsequently build the final dataset including the dependent, independent, and control variables.

4.7.1 Step 1 - Linking inventors to companies

First step is to ensure that the linkage between the disambiguated inventor dataset and the dataset containing owner companies for each patent was intact. This linkage between the datasets was generated by a python script developed by one of the authors who holds a master's degree in software engineering. The script serves the purpose to identify which patent and inventor is connected to which company. Table 4.3 presents one sample from each of the two datasets with the purpose to clarify which variables are used to link two datasets together. As seen in the table, there exists an overlap of 5 variables which ensures that the patent information in each of the datasets match and thus a linkage is made to a particular owning company. The final record is a merge between the two sets, where all fields in the table are relevant for the final analysis.

The script performs a four level validation process which is put in place to ensure that the linkage between a patent and its owning entity is robust. Only patents which passes top level validation is allowed to the next data process step. Top level validation entails that all of the five highlighted variables depicted in table 4.3 match. If these fields does not match we cannot ensure that the two data records refer to the same patent, and thus a linkage is not made. To ensure that the algorithm works as intended, a random sample of 50 matches were selected and manually validated by looking through all data available on ORBIS (2017) and determined whether correctly matched or not. This resulted in all 50 matches being correct and thus validating the functionality of the matching script.

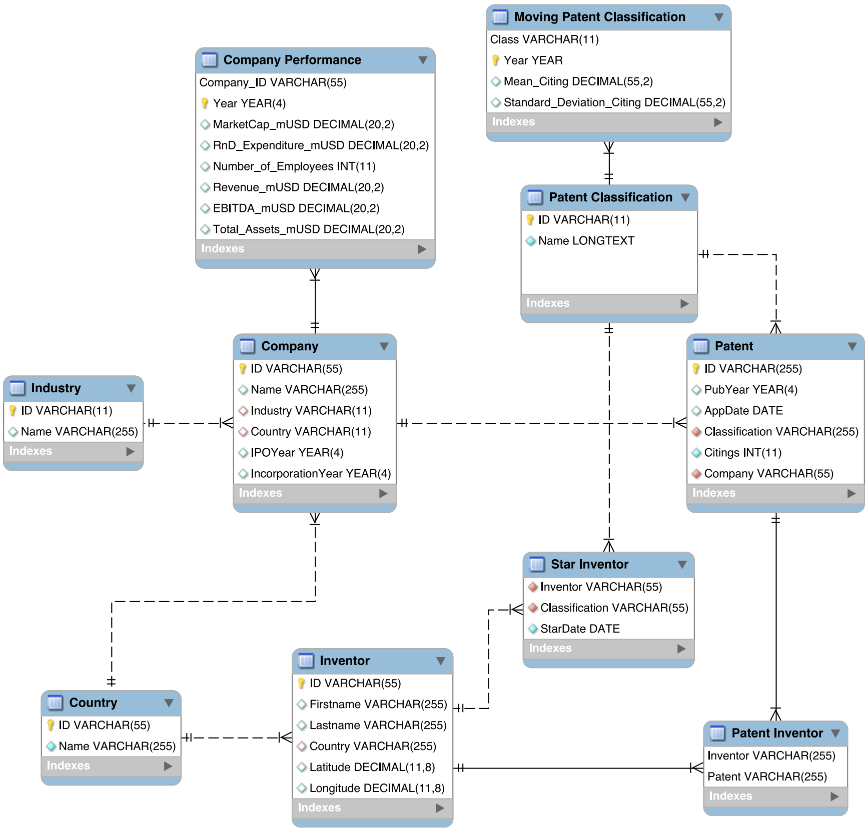

Figure 4.1: Main database

4.7.2 Step 2 - Constructing the database

The data in its raw format holds a low level of usability as it does not allow for versatile querying and data handling. This argues for the need of a normalized SQL database which allows for cross querying data and generating the final variables. Next step was to construct a database and normalize the data to allow for querying variables for the final analysis. Figure 4.1 shows an entity relationship diagram over the main database holding all information. The three main models are Company, Inventor, and Patent while the other models extend the information of these three. Most tables are self-explanatory while Star Inventor might need some explanation. This table simply holds the information of the date an inventor became a star inventor within a particular patent classification.

4.7.3 Step 3 - Scoring

After the SQL database was constructed, the process of scoring companies could begin. This was done through a combination of a python script and MySQL querying. These scripts will be found in the appendix. The process entails iterating through each company and the time span from the first patent until the last patent registered to the company. Next, an accumulated score based on all inventors employed each year at the company is compiled and linked to the company. Figure 4.2 presents the table created for building the company score. As seen each company was provided a score for each of the years in the time span between its first and last patent application date in the database created in step 2.

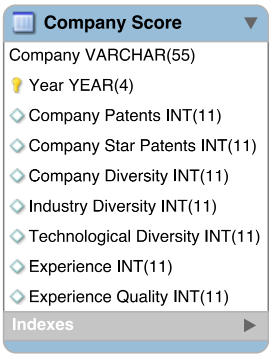

Figure 4.2: Company score table

Table 4.4 displays a 5 year sample taken for Apple Inc. In 1996 the company applied for 360 patents which would later be granted. The same year 236 different inventors worked with these 360 patents. 47 of these inventors are considered star inventors in that they have been previously involved in the creation of a star patent. In total the employed inventors have accumulated experience from 821 non-unique patents, i.e., two inventors may have worked on the same patent, however this is counted as two different experiences. In 1996 the inventors have previously worked in 247 companies. These are unique for each inventor, however two inventors may have worked in the same company which is counted as two different experiences. The same logic is applied for industries, star patents, and patent classes.

Company	Year	Company Patents	Company Star Patents	Company Diversity	Industry Diversity	Tech Diversity Diversity	Experience	Experience Quality
US942404110	1994	208	24	174	162	220	464	12
US942404110	1995	353	7	358	292	395	910	36
US942404110	1996	236	17	247	224	327	821	16
US942404110	1997	141	1	214	195	311	836	13
US942404110	1998	104	2	126	116	174	516	12

Table 4.4: Company score sample

4.7.4 Step 4 - Aggregating the score

The knowledge accumulated in a firm is arguably something that is used, and holds value, over a period of time, however it is not eternal. Argote (2012) discuss how organizational memory is imperfect which in turn results in a depreciation of knowledge over time. Katila and Ahuja (2002) presents a study which applied a five year depreciation window when observing knowledge value added through patents. This is further argued by Argote (2012) which suggests a significant knowledge depreciation after five years. For this reason a five year moving aggregation of patent score parameters is made. Table 4.5 presents the same company information as in the previous table, however the values are aggregated over a 5 year window. In 1996 the firm received a score which included the sum of previous 5 years.

Company	Year	Company Patents	Company Star Patents	Company Div.	Industry Div.	Tech Div.	Experience	Experience Quality	Years Included
US942404110	1994	632	104	567	493	589	1096	56	1989 1990 1991 1992 1993
US942404110	1995	946	101	879	752	952	1942	89	1990 1991 1992 1993 1994
US942404110	1996	1126	106	1058	919	1241	2665	104	1991 1992 1993 1994 1995
US942404110	1997	1205	100	1193	1055	1479	3388	104	1992 1993 1994 1995 1996
US942404110	1998	1210	84	1239	1097	1563	3779	102	1993 1994 1995 1996 1997

Table 4.5: Aggregated company score

4.7.5 Step 5 - Building the final analysis table

The final step was to build a table which held all dependent, independent, and control variables. These variables previously existed in the normalized database, however the final analysis required for a collated table to allow for the analysis to take place. Table 4.6 depicts the variable included in the final table.

Variable	Value
Company	US942404110
Year	2007
Industry	26
Country	US
Market Age	27
Company Patents	2,291
Company Star Patents	414
Company Diversity	3,987
Industry Diversity	2,966
Technological Diversity	5,195
Experience	22,298
Experience Quality	1,476
Total Assets	25,347
Number of Employees	23,700
Operating Revenue	24,578
R&D Expenses	782
EBITDA	4,714
Market Capital	133,464

Table 4.6: Final scores table

4.8 Statistical methods

As this study relies on the data to test the hypotheses, and subsequently the research question, it becomes imperative to apply a solid empirical data analysis process. This to ensure a high level of validity and reliability when drawing conclusions on the results. This section will present the methods applied to reach the results. Methods such as statistical modelling and validity analyses. Each serving the purpose to get a holistic understanding of the gathered data.

Statistical modelling entails the processes which seek to discover relationships and occurrences in the observed data. Depending on the interest of the particular study, different methods are available to discover such information. Regression analyses are responsible for recognizing relationships between variables, however the concept has a wide span and includes a vast amount of methods for analysing these relationships. Each method is available to ensure an appropriate application depending on the structure of the analysed data. The research field of econometrics often relies on the analyses of large datasets which span over a period of time, namely panel data (Gujarati, 2009), such is the case of this research.

4.8.1 Descriptive statistics

By listing the frequencies, distributions and other summarizing data information, the descriptive statistics serves the purpose to provide an overviewing understanding of the data used in this study. Specifically, the data will provide an understanding of the number of firms included in the study, their overall market capital distribution, experience and diversity characteristics, and other insight into the control variables. Furthermore, a frequency table of the industry distribution, as well as country distribution will give an understanding of the origins of the firms.

4.8.2 Panel data regression

To ensure coverage and robustness in the final conclusion, the research have constructed four separate regression model. Each model is implemented to serve the purpose to observe the data from several angles. This section will provide a granular explanation of each model, as well as their motivating factors for being included. There exists a number of regression analyses methods, one serving a different purpose than the other. The linear regression model is a commonly used method for identifying a linear relationship between one dependent variables and one, or more, independent variables. However, this model does not take time variant or individual variant aspects into account, i.e., data that includes a time axis for each observed individual. This study includes a panel dataset with observations made on individual spanning over a time period. To analyse such data, researchers are asked to apply a panel regression analysis. Depending on the data, there exists a number of methods for executing a panel regression analysis. For this study there exists three possible candidates for the analysis, namely an OLS-, fixed effect- (FEM), or random effects (ECM) model. Firstly, to understand whether or not to use an OLS model, it is imperative to know if there exists any significant panel effects in the dataset, if there is no difference a regular OLS model is sufficient as it does not take these effects into consideration. However, if there exists a significant difference, a FEM or ECM is the preferred choice. This can be measured by executing a Lagrange Multiplier (LM) Tests For Panel Models where the null hypothesis is that there exists no significant difference in the variance across entities, i.e., there is no panel effects (Breusch & Pagan, 1980).

Breusch-Pagan LM test for cross-sectional dependence in panels			
Model	*chisq*	*df*	*p-value*
OLS-Model	2043.5	1	<0.000***
alternative hypothesis: panel effects			
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.7: Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

Table 4.7 presents the results from executing the LM test. It can be seen that the results are significant, and thus the null hypothesis for the LM test can be rejected. These results indicate that there exists a difference in the variance across entities which entail that panel effects are present. For this reason an OLS model is not sufficient and a ECM or FEM is preferred.

Next step is to understand whether to execute the final tests using a FEM or ECM (Hausman, 1978). This is done by executing a Hausman test to see if the unique errors are correlated with the regressor. The null hypothesis for this test is that they are not correlated. If a significant value is found, a FEM is the prefered model to apply (Gujarati, 2009). This is done by executing a ECM and FEM, and then testing these against each other. Equation 4.6 and 4.7 displays the two models used for this test. It is worth noting that a FEM does not account for separate effects introduced in time-invariant variables such as industry or country. Instead, it assumes that these effects are included in the individual company, and that it should not account for such effects. In contrast, an ECM accounts for separate effects introduced by time-invariant variables.

$$
\begin{aligned}
\text{Market.Capital}_{it} = {} & \beta_1\text{Company.Diversity}_{it}+ \\
& \beta_2\text{Industry.Diversity}_{it}+ \\
& \beta_3\text{Technological.Diversity}_{it}+ \\
& \beta_4\text{Experience}_{it}+ \\
& \beta_5\text{Experience.Quality}_{it}+ \\
& \beta_6\text{Market.Age}_{it}+ \\
& \beta_7\text{Number.of.Employees}_{it}+ \\
& \beta_8\text{Company.Patents}_{it}+ \\
& \beta_9\text{Company.Star.Patents}_{it}+ \\
& \beta_{10}\text{Total.Assets}_{it}+ \\
& \beta_{11}\text{Operating.Revenue}_{it}+ \\
& \beta_{12}\text{Research.and.Development.Expenditure}_{it}+ \\
& \beta_{13}\text{EBITDA}_{it}+ \\
& \beta_{14}\text{factor}_{2008}+ \\
& \beta_{15}\text{factor}_{2009}+ \\
& \beta_{16}\text{factor}_{2010}+ \\
& \beta_{17}\text{factor}_{2011}+ \\
& \varepsilon_{it}
\end{aligned}
\tag{4.6}
$$

$$
\begin{aligned}
\text{Market.Capital}_{it} = \ \alpha + \ & \beta_1 \text{Company.Diversity}_{it} + \\
& \beta_2 \text{Industry.Diversity}_{it} + \\
& \beta_3 \text{Technological.Diversity}_{it} + \\
& \beta_4 \text{Experience}_{it} + \\
& \beta_5 \text{Experience.Quality}_{it} + \\
& \beta_7 \text{Industry}_{i} + \\
& \beta_8 \text{Country}_{i} + \\
& \beta_9 \text{Market.Age}_{it} + \\
& \beta_{10} \text{Number.of.Employees}_{it} + \\
& \beta_{11} \text{Company.Patents}_{it} + \\
& \beta_{12} \text{Company.Star.Patents}_{it} + \\
& \beta_{13} \text{Total.Assets}_{it} + \\
& \beta_{14} \text{Operating.Revenue}_{it} + \\
& \beta_{15} \text{Research.and.Development.Expenditure}_{it} + \\
& \beta_{16} \text{EBITDA}_{it} + \\
& \beta_{17} \text{factor}_{2008} + \\
& \beta_{18} \text{factor}_{2009} + \\
& \beta_{19} \text{factor}_{2010} + \\
& \beta_{20} \text{factor}_{2011} + \\
& \varepsilon_{it}
\end{aligned} \tag{4.7}
$$

Table 4.8 presents the results from executing the Hausman test by testing the two models shown in equation 4.6 and 4.7. The results indicate a significant correlation between the unique errors and its regressor, thus favoring a FEM for this study. However, as it is of interest for this study to account for country and industry, an ECM is executed to observe the coefficient values for the purpose of ensuring robust results.

Hausman Test		
Fixed vs Random effects model		
chisq	*df*	*p-value*
420.02	17	<0.000***
alternative hypothesis: fixed effects model		
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.8: Results from Hausman Test

Final models

After running the previously discussed tests to understand which model method is appropriate to implement, four separate models were included to understand the different effects. Table 4.9 presents the four models executed for this study.

	Model 1 *Fixed Effects*	**Model 2** *Fixed Effects*	**Model 3** *Fixed Effects*	**Model 4** *Random Effects*
Dependent Variable				
Market Capital	x	x	x	x
Independent Variable				
Company Diversity	x	x	x	x
Industry Diversity	x	x	x	x
Technological Diversity	x	x	x	x
Experience	x	x	x	x
Experience Quality	x	x	x	x
Control Variables				
Company Age		x	x	x
Market Age		x	x	x
Number of Employees		x	x	x
Company Patents		x	x	x
Company Star Patents		x	x	x
Total Assets			x	x
Operating Revenue			x	x
R&D Expenditure			x	x
EBITDA			x	x
Industry				x
Country				x

Table 4.9: Variables included in each model

Firstly, a model including only the independent variables is included to get an understanding of the R^2 value when observing only the relationship between these variables and the dependent variable. Model 2 includes non-financial variables which accounts for softer values within each firm. This is included to further understand the fit of this model when not accounting for hard financial values. Model 3 includes all variables presented in this study, both financial and non-financial values as well as all independent variables. This is the complete and most appealing model to observe. Model 1-3 are all fixed effects model, and neither accounts for the industry or country dummy variables, as it is assumed that these are controlled for when observing each individual firm. A fourth model is included to account for the two time-invariant variables country and industry. Model 4 is a random effects model which includes all variables, as model 3. It further accounts for effects caused by time-invariant variables.

Each model is also tested for heteroscedasticity, to understand the validity of the data. A Breusch-Pagan test have been carried out to understand the degrees of existing heteroscedasticity in the data. Heteroscedasticity explains the level of dispersion in the data. Figure 4.3 presents a visual example (not data from this study) of the occurrence of heteroscedasticity where there is a higher density of observations at X_1 in comparison to higher levels of X at X_2.

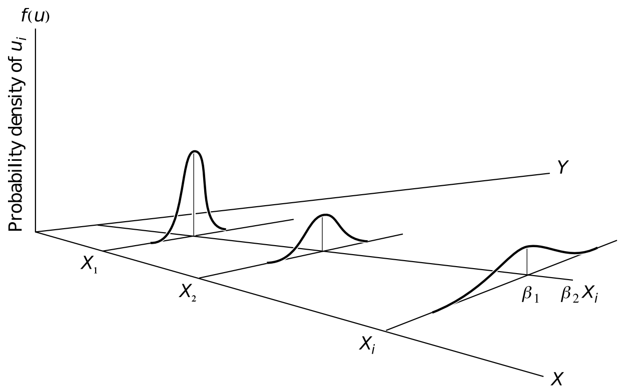

Figure 4.3: Visual example of heteroscedasticity occurence (Gujarati, 2009)

The Breusch-Pagan test seeks to understand if the data is homoscedastic or heteroscedastic. The null hypothesis of the test is that the data is homoscedastic. Homoscedasticity is desirable, however it is not necessarily ominus if the test indicated heteroscedasticity (Gujarati, 2009). Table 4.10 presents the results for each model. Each of the models show significant p-values which rejects the null hypothesis of the Breusch-Pagan test, indicating that all models hold heteroscedasticity.

Breusch-Pagan test			
for heteroscedasticity			
Data	*BP*	*df*	*p-value*
Model1	35530	15	<0.000***
Model2	86615	115	<0.000***
Model3	48600	111	<0.000***
Model4	48600	111	<0.000***
alternative hypothesis: heteroscedastic occurence			
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.10: Test for heteroscedasticity

Variance Inflation Factors *sqrt*	Model 1	Model 2	Model 3	Model 4
Company Diversity	7.737	7.222	7.719	16.106
Industry Diversity	11.898	11.857	12.044	20.461
Technological Diversity	10.296	10.779	11.594	16.711
Experience	4.883	4.755	5.113	10.027
Experience Quality	2.271	2.833	2.938	4.915

Table 4.11: Results from *sqrt(vif)*

Lastly, a test for multicollinearity was executed to understand the correlation between the independent variables. Multicollinearity is identified by observing the variance inflation factors (VIF). Table 4.11 presents the square rooted VIF values for each independent variable in each of the models. A general rule is that there is a high probability for the existence of multicollinearity if a value is above 2 (Kabacoff, 2015). In this case there is a multicollinearity problem for each independent variables in each model. This is further confirmed by table 4.12 which presents a correlation table of the correlation between the independent variables which show high correlation between all variables. This is further discussed in section 4.9.1.

Correlation Table					
	Company Diversity	**Industry Diversity**	**Technological Diversity**	**Experience**	**Experience Quality**
Company Diversity	1.000	-	-	-	-
Industry Diversity	0.995	1.000	-	-	-
Technological Diversity	0.985	0.990	1.000	-	-
Experience	0.945	0.955	0.968	1.000	-
Experience Quality	0.865	0.878	0.888	0.936	1.000

Table 4.12: Correlation table of the independent variables

4.9 Limitations

To fully comprehend aspects of credibility within this study, it is of interest to discuss certain limitations introduced by the method taken throughout this study. Saunders (2016) discusses three main quality aspects of research method, which are all discussed in this section in regards to this study.

4.9.1 Reliability

Saunders (2016) presents reliability as the extent to which the *"data collection techniques or analysis procedures will yield consistent findings"*. To ensure such consistency, researchers must take certain factors into consideration. Bryman and Bell (2015) discusses three prominent factors of reliability namely stability, internal reliability, and inter-observed consistency. Furthermore, reliability entails the degree to which the research can be replicated by other researchers. To cover replicability, the code resources can be found published on GitHub. However, due to copyright reasons, the raw database can not be published.

Stability refers to whether a measure is stable over time, i.e., if a measurement is executed on a group and then later re-administered at a later point in time, there will be little fluctuations in the new results compared to the previous ones. It is hard to ensure that this will be the case, as market performance, demand, and the importance of particular firm aspects, e.g. knowledge, varies over time. However, as the study holds strong ground in patent information, this aspect has been taken into consideration. Patent production always has, and will most likely continue to require experienced inventors, who hold certain levels of the variables observed in the study, which argues for the stability of the measurements made.

Further, internal reliability refers to the intercorrelation between variables, which is relevant for studies that apply questionnaires, where researchers may ask two questions which answer the same thing. However, in the case of this study, a test of the multicollinearity between the independent variables can be executed to explain how much the variables depend on each other (Gujarati, 2009). (Kmenta, 1997, p431) states that *"multicollinearity is a question of degree and not of kind. The meaningful distinction is not between the presence and the absence of multicollinearity, but between its various degrees"*. Thus, it is important to state that multicollinearity will exist amongst the independent variables. However, the question is about how much. If a high level of multicollinearity exists, several remedies exist to counter the phenomena. Saunders (2016) presents the *"do nothing"* school of thought, which argues that researchers sometimes have no choice over the data available for the empirical analysis. The author states that *"multicollinearity is God's will, not a problem with OLS or statistical technique in general"* (Gujarati, 2009, p342). The "do nothing" school of though, is the approach taken for this research, as the data available is limited. Furthermore, (Gujarati, 2009, p347) states that *"if the sole purpose of regression analysis is prediction or forecasting, then multicollinearity is not a serious problem because the higher the R2, the better the prediction"*. As this study seeks to predict what effects diversity and experience variables have on the market capitalizations of firms, this statement suggests that multicollinearity is not of a particular threat of the study. It is expected, and to some degree desired, to find interdependence amongst the independent variables, as they seek to measure the same originator variables, namely diversity, and experience. Furthermore, it is worth noting that diversity is dependent on the experience, as without experience an individual cannot hold any level of diversity. To ensure that collinearity does not pose a serious problem it is imperative that the R2 is reasonably high and that the coefficients hold individually significant results (Gujarati, 2009).

Inter-observed consistency refers to the degree of which observers can agree on the meaning of what they are observing (Bryman & Bell, 2015). For this study, there exists a risk in that observers may believe that the diversity and experience metrics do not adequately measure what they intend to. This has been mitigated by coupling the hypotheses to previous literature.

This study accounts for one aspect of patent quality which may impact market value, namely patent citations. However, there exist additional heterogeneity aspects of patents not taken into consideration in this research. Such as the patent's monetary value, novelty, etc. Scholars argue for the impact such quality aspects might have on market value and could be a possible factor which might influence the outcome of the applied regression models (Ernst, 2001; Hagedoorn & Cloodt, 2003). Furthermore, patent protection differs between industries and in circumstances where they offer weak protection the willingness to file a patent application may be low. An implication of this is that a patent can be a poor proxy of the firm's knowledge in those industries as there might exist other innovation outputs than patents (Ernst, 2001). This implication is somewhat taken into consideration by incorporating the industry dummy variable into one of the regression models.

4.9.2 Validity

Literature presents several aspects of validity, as it is a highly disperse quality factor which includes several aspects of the applied research method (Bryman & Bell, 2015; Saunders, 2016). Depending on the nature of the executed research method some aspects may be more critical to take into consideration than others. Often these differ significantly between qualitative and quantitative studies as they differ greatly in their epistemological and ontological assumptions, which argues for a bespoke approach when discussing the validity of this study (Whittemore, Chase, & Mandle, 2001).

For this study, validity is related to the chosen method's ability to identify a causal relationship with the population studied. This research has undergone several systematic steps with the intention of generating an unbiased method to study the subject to ensure internal validity. Firstly the body of literature studied sought to generate an in-depth understanding of different aspects of the independent variables. By not only taking on favorable beliefs of what the effects may be but rather taking several polarized points into considerations to ensure unbiasedness in the final analysis. This literature constructed a foundation of generating the hypotheses and further the independent variables. Furthermore, the data collection presented an impartial systematic process to produce the final results without removing certain groups which would possibly introduce bias. To statistically identify how well the sample variables represents the population one can observe the standard error derived from the executed regression models. These figures explain how well the coefficients explain the population's behavior, where a lower standard error hints for a better representation of the population behavior. Further analyses have been made to understand the validity of the statistical tools.

The executed Breusch-Pagan indicated heteroscedasticity in each of the models. Although homoscedasticity is desirable, (Gujarati, 2009, p592) presents statements made by Baltagi, that there is bound to be heteroscedasticity present in panel data. To adjust for such occurrences, other predictors can be incorporated into the regression models. As the predictors used for this study are imperative to use for conducting the research, it is difficult to change these due to the constraining availability in the data sources which restricts the study to take any remedial actions if heteroscedasticity is present in the used dataset.

To ensure conclusion validity, different models have been constructed. These models take different aspects into consideration and include different types of control variables. Furthermore, as there exists two prominent approaches of conducting regression testing on panel data, namely a fixed effects model and a random effects model, this research have applied both to observe effects depending on the angle the model takes.

4.9.3 Generalizability

Generalizability, also known as external validity, refers to the degree at which research can generalize its findings beyond the boundaries of its particular context (Bryman & Bell, 2015). This research has taken several actions to ensure a high level of generalizability as patent usage is widely spanning and may be of relevance for several industries, as well as, several firm sizes. This has been done by constructing statistical models which include control variables to for adjust for effects introduced by grouping variables such as firm size, company, or industry. One aspect where this study is lacking generalizability is in the subjects from which the independent variables derives from, namely the inventors. The inventors who are observed in this study, are not all inventors, but rather a subset of inventors. This subset includes inventors which adhere to specific inclusion constraints, namely inventors who have been involved in a patent application at a specific point in time. There may exist a larger set of inventors in the companies observed which are not taken into consideration due to the limitations in the data. Ernst (2001) discuss how not all inventions are patentable and not all patentable inventions are patented. This suggests that there may exist more inventors within companies which are not included in this particular study which limits the generalizability of the results.

The quantitative nature of this study seeks general understandings, which typically comes with the sacrifice of not providing any case specific insights. As a logical consequence, the results from the statistical tests will provide general insights, and can thus not be used to exclude any case specific occurrences of the contrary to what the findings will show. Furthermore, as the study makes a bold attempt at explaining the impact of individual-level variables on firm-level variables, it is difficult to ensure an explanation of the causality of the results. However, this is preemptively countered by carefully selecting variables which hold ground in previous research.

5

Results

This section seeks to present the empirical results from executing the data analysis. Section 4.8 presented detailed information regarding the process of analyzing the data, while this section merely aims to present the results in its raw format without introducing any interpretation of the figures. Initially, the descriptive statistics will be presented. Furthermore, the analysis seeks to test the hypotheses presented in section 3.2.2.

5.1 Descriptive statistics

Table 5.1 presents the descriptive statistics of the data set. There are 3,376 companies present in the data. Each company has available data spanning on average over 2.699 years. There are companies from a total of 74 industries and 45 countries. *N* explains the number of observations within each variable, where a company may have more than one observation. A company has on average been publicly listed for 14.062 years. The most valuable company has a market capital of m$US 625,349.00. The average company has 13,753 employees and spends m$US 177.874 on R&D annually.

Statistic	N	Mean	St. Dev.	Min	Max
Company	3376	–	–	–	–
Year	10,936	2.699	1.434	1	6
Market Age	8,681	14.062	14.932	0	120
Market Capital	6,943	7,661.299	27,486.180	0	625,349
Company Diversity	10,936	292.210	1,619.078	0	45,171
Industry Diversity	10,936	220.925	1,297.771	0	40,019
Technological Diversity	10,936	453.758	2,973.258	0	92,215
Experience	10,936	1,708.613	12,308.880	0	421,911
Experience Quality	10,936	55.524	329.679	0	9,716
Company Patents	10,936	161.227	983.964	0	29,443
Company Star Patents	10,936	3.406	26.235	0	800
Number of Employees	9,026	13,763.680	59,996.070	0	2,100,000
Total Assets	10,656	8,172.960	57,397.200	0	2,268,347
Operating Revenue	10,766	4,900.409	21,350.890	−0.87	467,029
Research and Development Expenses	8,603	177.874	735.461	−60.79	10,772
EBITDA	10,314	825.901	3,742.463	−9,637.00	78,669

Table 5.1: Descriptive Statistics

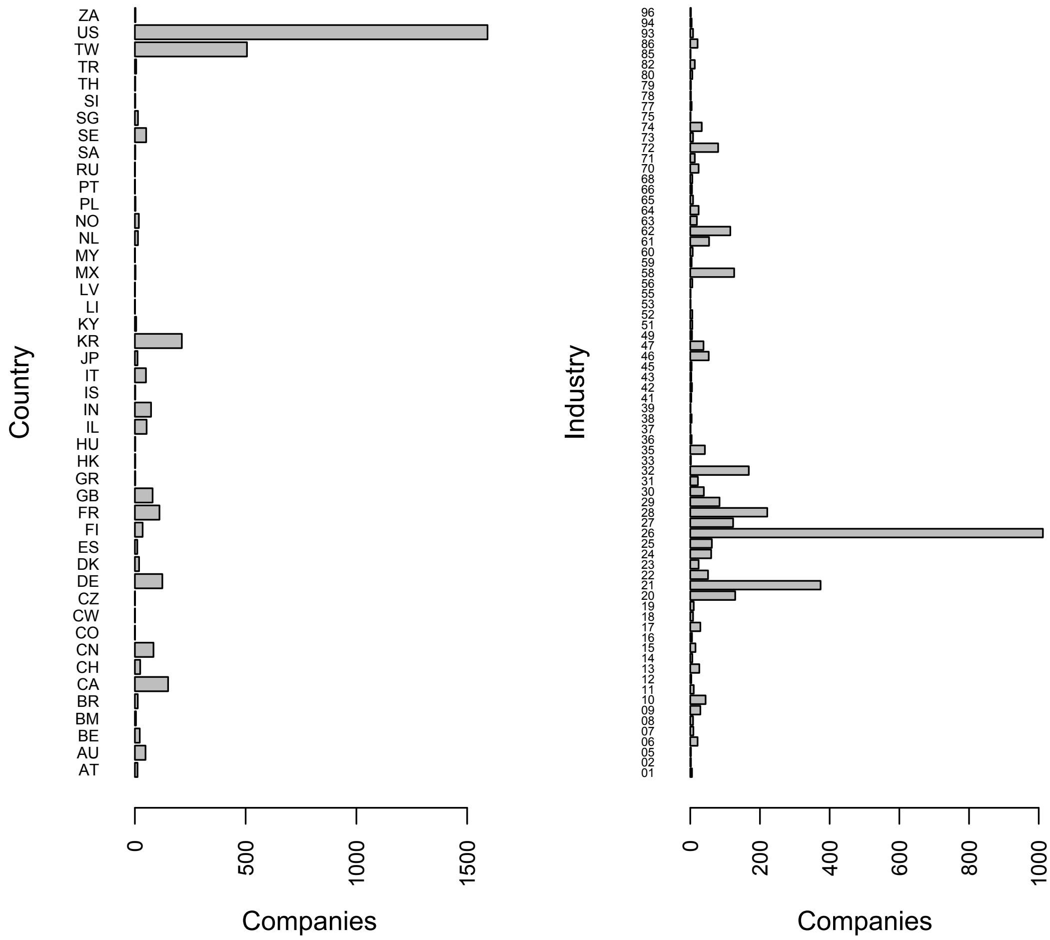

Figure 5.1: Country and Industry Density

Figure 5.1 display two density tables. The tables present the frequency of companies in an industry or country. Most companies are active in industry NACEv2 category 26, namely "Manufacture of computer, electronic and optical products". This reveals that most of the companies in the final data are active in this industry. The chart on the left reveals that most companies in the dataset are registered in either United States or Taiwan.

5.2 Hypothesis testing

Figure 5.2 presents all the resulted coefficient values from running the empirical analysis. Each model is presented in each of the four columns 1-4. As all models differ in which type of variables are included, it can be observed that model 2 and 3 have coefficient values missing in contrast to models 1 and 4. Further, for the purpose of readability, the industry and country-specific variables have been collapsed as the individual coefficients of each are not of any particular interest for this study. Notably, only model 4 have the industry and company specific variables included. The missing coefficients are all discussed in section 4.8.2. All models hold different observation sizes due to the availability of complete data overall predictors. Model 1 holds the most observations as it only requires the observations to include market capital and all independent variables. In contrast, model 3 and 4 include the least amount of observations as the models require each observation to include complete annual information for all independent variables and control variables. The F-statistics of all models holds highly significant p-values ($p < 0.01$) which indicate that the individual coefficients can be interpreted correctly and that the values have a significant joint impact. Furthermore, it can be observed that the R^2 value increases for each additional predictor in the model. Model 1 has an overall fit of $R^2 = 0.209$, whereas model 2 and 3 has $R^2 = 0.315$ and $R^2 = 0.630$ respectively. These values suggest that Model 3 has the greatest fit of each fixed effects model, rendering it most suitable for interpreting the results from the independent variables. As previously discussed in section 4.8.2, the Hausman test suggests that a fixed effects model will show unbiased values and is thus most suitable, however, to ensure robustness a random effects model is included.

	Dependent variable:			
	Market Capital (m$US)			
	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Random Effects Model
	(1)	(2)	(3)	(4)
Independent Variables				
H_1Company Div.[1]	-12.434^{***} (2.417)	-30.747^{***} (3.320)	-19.998^{***} (2.898)	-8.338^{***} (2.330)
H_2Industry Div.	37.682^{***} (4.260)	47.216^{***} (6.042)	32.429^{***} (4.950)	25.363^{***} (3.474)
H_3Tech Div.	-21.574^{***} (1.889)	-17.416^{***} (2.854)	-6.162^{**} (2.483)	-6.929^{***} (1.236)
H_4Exp.[2]	1.868^{***} (0.264)	3.569^{***} (0.348)	1.132^{***} (0.293)	-0.027 (0.161)
H_5Exp. Quality	92.233^{***} (3.990)	99.430^{***} (6.416)	51.908^{***} (5.290)	27.236^{***} (2.949)
Company Div.:Industry Div.	-0.001^{***} (0.0002)	0.003^{***} (0.0004)	0.002^{***} (0.0004)	-0.00004 (0.0003)
Company Div.:Tech Div.	0.001^{***} (0.0001)	0.0004^{*} (0.0002)	-0.00001 (0.0002)	0.001^{***} (0.0001)
Industry Div.:Tech Div.	0.0001 (0.0001)	-0.002^{***} (0.0003)	-0.001^{***} (0.0002)	-0.001^{***} (0.0002)
Exp:Exp Quality	-0.0002^{***} (0.00002)	-0.00003 (0.0001)	0.0001 (0.0001)	-0.0001^{**} (0.00004)
Company Div.:Industry Div.:Tech Div.	0.000 (0.000)	-0.000 (0.000)	0.000^{*} (0.000)	-0.000 (0.000)
Control Variables				
Market Age		433.125^{***} (152.781)	296.750^{**} (130.878)	49.802^{***} (19.274)
Number of Employees		0.143^{***} (0.016)	0.082^{***} (0.014)	-0.025^{***} (0.008)
Company Patents		-17.747^{***} (2.212)	-8.029^{***} (1.747)	-3.949^{***} (1.268)
Company Star Patents		-16.705 (19.146)	-51.219^{***} (14.959)	65.908^{***} (11.027)
Total Assets			0.056^{***} (0.017)	-0.0003 (0.015)
Operating Revenue			-0.343^{***} (0.030)	-0.186^{***} (0.022)
Research and Development Expenses			0.495 (0.865)	4.366^{***} (0.451)
EBITDA			5.640^{***} (0.132)	5.774^{***} (0.110)
Time Invariant Variables				
Industries				*Included*
Countries				*Included*
factor(Year)2008	$-3{,}253.144^{***}$ (310.265)	$-3{,}568.137^{***}$ (362.914)	$-2{,}673.218^{***}$ (301.463)	$-2{,}275.994^{***}$ (320.112)
factor(Year)2009	$-1{,}904.193^{***}$ (328.668)	$-2{,}811.587^{***}$ (420.856)	$-1{,}474.954^{***}$ (353.240)	-711.633^{**} (332.183)
factor(Year)2010	$-1{,}083.537^{***}$ (356.417)	$-2{,}713.302^{***}$ (515.640)	$-2{,}045.338^{***}$ (435.176)	-948.690^{***} (356.319)
factor(Year)2011	$-1{,}365.319^{***}$ (416.451)	$-3{,}899.975^{***}$ (633.269)	$-3{,}130.041^{***}$ (534.765)	$-1{,}677.354^{***}$ (410.015)
factor(Year)2012	$2{,}929.393^{***}$ (661.150)			$1{,}507.111^{**}$ (641.995)
Constant				$14{,}679.390^{**}$ (5,784.856)
Observations	6,943	5,091	4,176	4,176
R^2	0.209	0.309	0.625	0.762
Adjusted R^2	-0.133	0.016	0.464	0.756
F Statistic	85.314^{***} (df = 15; 4849)	88.879^{***} (df = 18; 3574)	221.200^{***} (df = 22; 2917)	117.543^{***} (df = 111; 4064)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5.2: Results from statistical execution

The initial 5 variables are aimed at testing the hypotheses of this study. Further 5 variables are the interactions between the independent variables. The results for the hypothesis tests are:

H_1 *A higher level of individual-level company diversity has a positive impact on firm performance.*

The results in table 5.2 show highly significant results ($p < 0.01$) for all four models. These results indicate that the null hypothesis is rejected, and suggests that individual-level company diversity has an impact on firm performance. The coefficient values are present to obtain an understanding if that impact is negative or positive. The coefficient values in each of the model show that individual-level company diversity has a negative impact on firm performance. As H_1 is incorrect as it anticipated a positive impact whereas the model shows significant negative coefficient values. To exemplify, these results say that if a firm employs an inventor who has filed a patent application for one previous company before her first patent application in the new firm, the market value of the new firm is impacted by million $US -19.998 (coeff from Model 3).

H_2 *A higher level of individual-level industry diversity has a positive impact on firm performance.*

Table 5.2 show highly significant ($p < 0.01$) results for all models, thus rejecting the null hypothesis and indicating that individual-level industry diversity has an impact on firm performance. Further, the coefficients show that industry diversity indeed has a positive impact on firm performance, suggesting that H_2 is correct in its assumption. Let's continue with the inventor from the previous example. If the former firm she worked in were mainly active within another industry, the market value of the new firm would be impacted by million $US 32.429 (coeff from Model 3).

H_3 *A higher level of individual-level technological diversity has a positive impact on firm performance.*

The final diversity hypothesis test regards technological diversity. Table 5.2 show highly significant results ($p < 0.01$) for all four models which results in a rejection of the null hypothesis and suggests that individual-level technological diversity has an impact on firm performance. H_3 assumes that individual-level technological diversity has a positive impact on firm performance, whereas the coefficients from all four models reveal that individual-level technological diversity has a negative impact on firm performance. Therefore, H_3 is incorrect in its assumption. Once again, if the inventor, from the previous example, is involved in a patent application within a new patent classification field, the market capital of the new firm is impacted by million $US -6.162 (coeff from Model 3).

H_4 *A higher level of individual-level patent experience has a positive impact on firm performance.*

The first of two hypotheses regarding experience, seek to test whether individual-level patent experience has a positive impact on firm performance. Model 1-3 all show significant results which result in a rejection of the null hypothesis, hence indicating that individual-level patent experience has an impact on firm performance. Whereas Model 4 show insignificant results and can for that reason not reject the null hypothesis. This result renders the model's coefficient value irrelevant to regard. Judging solely by the significant coefficient values of Model 1-3, it can be observed that individual-level patent experience indeed has a positive impact on firm performance. For each additional patent application, an inventor has made previous to a new patent application, the market value of a firm at which the inventor is employed will be impacted with million $US 1.132 (coeff from Model 3).

H_5 *A higher level of individual-level patent experience quality has a positive impact on firm performance.*

The last hypothesis to test regards the individual-level patent experience of inventors. All models show significant results which allow for a rejection of the null hypothesis. These results indicate that individual-level patent experience has an impact on firm performance. H_5 assumes that individual-level patent experience has a positive impact on firm performance. It is recognized that individual-level patent experience has a positive impact on firm performance indeed, when observing the coefficient values of each model. For each previous star patent, an inventor has been involved with previous to a patent application in a firm, the market value of that firm is impacted by million $US 51.908 (coeff from Model 3).

6

Discussion

The objective of this research has been to examine the relationship between the individual-level background variables: functional diversity and experience, and firm performance. By doing so, this research seeks to expand the theory concerning individual attributes that may affect a firm's competitive advantage, a level of analysis that is claimed to have gotten too little attention in the knowledge-based view (DeCarolis & Deeds, 1999; Ernst, 2001; Felin & Hesterly, 2007). Previous research on individual-level variables is limited and sometimes contradictory, which has led us to include research that is closely related but not a perfect fit for our scope and research question. However, the combined assessment of the reviewed literature has led us to develop hypotheses expecting a positive correlation between both individual-level functional diversity and individual-level experience.

6.1 Diversity

This study approaches the concept of functional diversity at the individual-level and further aims to decompose the lumped perspective of the concept most often used in literature (M. D. Mumford, 2012). The diversity of knowledge has been argued to possibly allow team members to leverage on the cross-section of their previous experiences to stimulate creativity. Where creativity has been argued as an enabling factor for individuals to generate new ideas and to define and solve complex problems, the research aims to gain a wider understanding to the accuracy of these claims (M. Mumford & Gustafson, 2007; M. D. Mumford, 2012). By limiting functional diversity to job-related experience, an initial step is taken towards a tapering of the final measurement points examined in the regression analysis, namely company diversity, industry diversity, and technological diversity. The statistical models testing the hypotheses resulted in dispersed observations differing from the expectations derived from literature, with some diversity variables having a negative impact on firm performance. Initially, the study took a positive stance on all of the diversity variables, as literature mainly recognizes diversity as something positive for firm performance with regards to creativity and innovation (Kristinsson, Candi, & Sæmundsson, 2016; Lettl, Rost, & Von Wartburg, 2009; M. D. Mumford, 2012; Woodman, Sawyer, & Griffin, 1993). Further studies have proven that these benefits are predominantly connected to functional diversity. Worth noting is the literature's general tendency of analyzing functional diversity at a group level to demonstrate that relationship. Nevertheless, a few attempts have been made to explore the relationship at an individual level. Verhoeven (2015) provides results showing that functional diversity in technical domains has a positive effect on novelty in innovative performance. Yap et al. (2005), provides further findings in support of a positive correlation, however through examining the innovative performance of management teams and not individual innovators as in this study.

Hypothesis 1, which states that individual-level company diversity has a positive impact on firm performance, was found to be incorrect. Although the significant results rejected the null hypothesis, the coefficients indicate that individual-level company diversity has a negative impact on firm performance, which contradicts the assumption of the hypothesis. The observed negative relationship between individual-level company diversity and firm performance counters the general assumption found in the literature of functional diversity as something positive (Verhoeven, 2015; Yap, Chai, & Lemaire, 2005). However, most identified literature have taken a lumped view on functional diversity where granular measures, such as previous company experience, has not been accounted for (M. D. Mumford, 2012). The discussion regarding human resources may hold a possible explanation for these contradicting findings. Campbell et al. (2012) states that firm-specific human capital, embodied in employees as tacit knowledge, is the core of competitive advantage, and protected from competitors by its applicability in the firm-specific context alone. Moreover, a firm's innovative capability can be seen as a construction of the firm-specific human capital and is typically assumed to take several years to develop (Yap, Chai, & Lemaire, 2005). Through this perspective, a high level of company diversity is an expression of an individual's past movement between companies. Furthermore, a high individual-level company diversity score should indicate that the inventor has spent fewer years in each company and thus a reduced contribution to the firm-specific human capital would have been made. If individual-level diversity refers to generalists, the opposite is considered specialists, which, according to the findings, would be preferred in the context of company experience. Verhoeven (2015) and Olson et al. (1995) provides additional perspective to this discussion. The authors identify a context where functional diversity is seen as beneficial, namely when the objective is to produce novel inventions. However, the benefits of diversity are not as apparent when the requirement of novelty is less pronounced, as in the case of incremental innovation. Such novelty aspects have not been taken into account when conducting this study, and thus a rejection of their findings is not warranted. This study can merely seek to stimulate a discussion of the subject, where scholars should proceed with caution when drawing definite conclusions regarding the benefits of individual-level company diversity.

Hypothesis 2 assumed that individual-level industry diversity has a positive impact on firm performance. The results derived from the statistical models indicated that this assumption is correct, with highly significant and positive coefficients. In line with these findings, literature has previously taken a positive stance on functional diversity (Kristinsson, Candi, & Sæmundsson, 2016; M. D. Mumford, 2012; Y. Zhang, 2016). Hülsheger et al. (2009); M. D. Mumford (2012) have a positive attitude towards functional diversity, established by its boosting effects on creativity. Furthermore, other beneficial factors of functional diversity include improved networks and contacts, expertise, and larger knowledge pools. The authors identify industry as one of the prominent explaining factors of functional diversity, through stimulating creativity causing a positive impact on inventiveness and innovation (Harrison & Klein, 2007; Kristinsson, Candi, & Sæmundsson, 2016). The positive effect of individual level industry diversity is interesting since it highlights the positive experience an inventor can bring along and exploit in a new context. Except for the effect of knowledge transfer providing a far-reaching knowledge pool, possible to utilize in the innovation process, diverse knowledge can also provide indirect access to new knowledge through the assumed gain of heterogeneous networks provided by multi-industry experience (Østergaard, Timmermans, & Kristinsson, 2011). A similar observation has been made by Hülsheger et al. (2009) which states that functional diversity triggers communication with the external environment outside the team setting. A perspective which suggests that access to more diverse knowledge provides an increased number of possible combinations and applications in the innovation process (Østergaard, Timmermans, & Kristinsson, 2011). A further potential explanation suggested by Østergaard et al. (2011), is that diverse knowledge bases increase an organization's absorptive capacity, making it better suited to exploit both internal and external knowledge through improved learning and interaction.

Hypothesis 3 assumes a positive relation between individual-level technology diversity and firm performance. The results from the statistical models indicate a significant negative relationship between the two variables, rendering this assumption false. A negative correlation implies that employees with expertise in a certain technological field create the most value for the company if they keep working within that particular field. Although a vast amount of diversity theories (e.g. Kristinsson et al. (2016); M. D. Mumford (2012)) suggests that functional diversity has a positive effect on creativity and innovative capacity, however, the findings implies that such assumptions can not be made in the context of this research. The negative impact of technological diversity may have a possible explanation in Grant (1996, 2016)'s claim that individual specialization is necessary due to the increased complexity of technology. Simon's (1955) theory of bounded rationality can also help to shed light on the issue, as the author argues that the limitations in human cognition favors specialization due to difficulties in processing and acquiring diverse knowledge. The interpretation of the negative effect on firm performance can extend outside the boundaries of diversity theory. More specifically, the findings seem logical when discussed in the context of theories regarding learning curve effects (David, 1973; Wright, 1936). By doing something over and over again, the likelihood of errors will decrease. Jain (2013) identifies the presence of a learning curve within R&D and innovation production. The author finds that repeated work in patent production has a positive effect on production efficiency, which suggests that the longer an inventor works, and hence more repetition of activities, within a technological field, the more efficient the output will become. However, as innovation is per definition something that requires the generation of something novel and is not repetitive per se, this finding assumes that patent production within the same technology will include repetitive activities connected to the innovative work process. Similarly, Lettl et al. (2009) found negative effects of functional diversity on the performance in independent innovators in the context of medical equipment technology. As a possible explanation for their result, the authors state that diversity provide too many perspectives, making it difficult to identify the optimal solution. The results from testing H_3 does not deny the existence of positive effects of technological diversity at an individual level but concludes that they are not enough to compensate for its drawbacks when regarding a firm's market capitalization. The results of this study could appear to be contradictory when contrasted with the findings of Verhoeven (2015) which show a positive correlation between the creation of novel inventions and individual diversity in technological domains. However, the patent data implemented in the analysis cover the whole spectra and contains no granular information regarding the novelty of the inventions. Consequently, the result is not necessarily in conflict with Verhoeven's (2015) findings, rather it brings further clarity to the subject by favoring technological specialization over diversity in general.

Conclusively, the findings have shown to relate to the knowledge-based view through the facet of human capital and its inherent value found in its long development time and importance for long-term competitive advantage. The statistical tests provided intriguing results in the contrasts between company diversity and industry diversity, where one is found to be negative and the other positive for firm performance. However, the negative impact of technological diversity argues that technical specialists are more valuable for companies than technical generalists. Arguably, a company would reap most benefits when employing an individual who has previously been working in another industry with the same particular technology. To demonstrate, a car manufacturer would presumably benefit from hiring a software engineer from the communication industry when seeking to innovate in the field of connected vehicles, as they can leverage on their previous technological expertise in a new industry. In general, the results from testing individual-level functional diversity variables suggest that a company should strive to have a low employee turnover in regards to their employees involved with innovation production. By doing so, the firm should aim to minimize the impact on the individual's company diversity and reap the benefits from increasing the individual's firm-specific knowledge within their field of expertise.

6.2 Experience

Identifying the effects of individual-level experience allows for an understanding of whether a firm would benefit from employing experienced inventors. Previous research have discussed how learning curve effects impact production, where Wright (1936) firstly identified learning effects in the aviation industry. Discussed in previous chapters, this research have found an existing consensus in literature which argues that individual-level experience have a positive impact on the production output, both in innovation and manufacturing. Conti et al. (2013) presents a study which identified that there is a higher probability of producing breakthrough inventions the more experience an inventor possess. The authors identify a breakthrough invention by observing a patents economic and technological contribution, as well as its citation count. Furthermore, Hall et al. (2005) identifies that patent citations have a positive effect on firm performance, thus suggesting that the patent quality is imperative for companies. Based on this, an interesting point to explore is how the quality of an individual inventors experience impacts the firm at which the inventor is employed.

Hypothesis 4 sought to identify whether the effect of experience on firm performance is positive. Three out of four models had significant results which indicate that experience indeed has an effect on firm performance, and that the effect is positive when observing the coefficient values of each significant result. One of the models had insignificant results, and can thus not reject the null hypothesis by itself rendering the coefficient value irrelevant. These findings are inline with what previous research suggests. Previous research found that a number of output factors benefits from having experienced individuals performing production, in this case patent production. Factors such as efficiency, found in the article presented by Jain (2013), as well as breakthrough rate identified in the research conducted by Conti et al. (2013). These findings indicate that firms would benefit from having inventors who hold a higher degree of patent experience.

Lastly, hypothesis 5 aimed at understanding the effect of experience quality on firm performance. Previous research suggests that patent quality, the metric used for experience quality in this study, has a positive impact on the owning firm's market value (Hall, Jaffe, & Trajtenberg, 2005). Previous knowledge theory regarding tacit knowledge argue that individuals accrue unconscious knowledge over time (J. R. Howells, 2002). This may suggest that individuals accumulate an unconscious understanding of how valuable patent production is executed. The statistical models resulted in highly significant results which indicate that there is an effect on firm performance introduced by experience quality. Looking further on the coefficient values, it can be observed that they have a high positive impact on firm performance. These results suggests that indeed, an inventor who holds experience of patenting inventions which holds high quality, in the form of patent citations, does impact the firm performance.

7

Conclusion

Inspired by the knowledge-base view and research on diversity and experience relatedness to knowledge production, this study has examined how individual-level experiences relate to firm performance. This study observes an extensive set of innovators in a wide range of industries from all over the world. The observations are made on patent inventors and their employing company. By executing regression tests on large panel data sets looking at individual-level knowledge characteristics and firms' market value, the study found that diverse industry experience is beneficial at an individual level, and has a positive effect on firm performance. The opposite relation holds for high degrees of diversity in technology experience and company experience, where generalists are found to have an adverse correlation with firm performance. Furthermore, this study has shown a positive effect on firm performance from individuals with a track record of patent production. Also, individuals with a history of producing high-quality patents have proved to be valuable for a company as they have a positive impact on firm performance. The findings of this study add to the body of research striving to understand how individual characteristics relates to innovative work and in extension impacts firm performance. The addition is the claim that individual-level functional diversity is not incontestably beneficial for the performance of a firm, and caution has to be taken when considering the diversity amongst the individuals providing the innovation production within firms. However, experience and its quality holds strong evidence for being valuable for the innovation work force.

8

Future Work

This study has identified few subjects of interest for future research. As this study takes a quantitative approach, there exists a window for qualitatively observing cases in which individual-level knowledge factors may impact the innovative performance of a firm. Therefore, a suggestion is made for future researchers to conduct a multiple case-study to observe the innovativeness of individuals, active in innovation production, with heterogeneous and homogeneous experiences, where the cases are studied to understand how individuals may leverage their previous experiences to benefit the innovative output. This could assist in understanding how individual-level knowledge assets should be allocated and employed by firms to improve the overall innovativeness and further enhance firm performance.

Possible relatedness effects between the experiences individuals' have accrued from industries, technologies, and companies, have not been explored in this research. Situations where two technological fields may be less or more related to each other and thus allowing inventors to leverage differently on their previous experience. Therefore inviting future researchers to explore how variations in relatedness within the individual-level diversity variables may affect the performance of these individuals, and subsequently the firms. Relatedness is just one of many aspects to consider when exploring the data.

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