THE ETERNAL QUEST FOR NOVELTY:

A DIFFERENT VIEW ON THE ECONOMIC VALUE AND RISKS ASSOCIATED WITH THE SEARCH FOR NOVELTY

BERNARDO CANTONE

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SPRU – Science Policy Research Unit

University of Sussex

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Signature…………………………….

University of Sussex

Bernardo Cantone

Doctor of Philosophy in Technology and Innovation Management

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Summary

Novelty is widely acknowledged to be key in the growth and prosperity of firms. However, the multifaceted and complex characteristics that govern novelty processes can also link it to both diminution in value and failure. Not all novel inventions are valuable and not every valuable invention is novel, and the associated risks and uncertainty remain inherent to the value-creation process. Firms should carefully balance the potential benefit of novelty with the potential to incur a certain degree of risks. In general, the nature of duality in novelty stimulates the need for a better understanding of the impact and risks associated with firm's generation of novelty.

This doctoral thesis synthesises the multitude of insights, ideas and approaches related to novelty processes. It then goes a step further by deepening the empirical research into the technical and social contexts of novelty. It links firm-level processes of knowledge-search with invention-level *ex-ante* novelty indicators, to consider the value of novelty from a variety of different perspectives. It explores the value and the risks associated with both technological novelty and firm search processes through distinct novel approaches. The economic impact is assessed through the analysis of the shift in market value after the moment of disclosure of patenting inventions. The side effect is assessed through the investigation of the hazard of firm failure.

Despite the strong potential which novelty represents for the generation of breakthrough innovation, the thesis argues that its tangible economic impact is sporadic and rare. Based on the same premise, the thesis argues it involves substantial risks. The empirical evidence suggests that novelty only marginally encourages investors in further financing of the firm. Whereas the firm survival analysis shows that novelty significantly increases firm failure rate, and it does not increase leverage for merger or acquisition.

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Chapter I

INTRODUCTION

1. Thesis Overview

Novelty is an essential part of technological progress and value creation. At the same time, novelty implies risk and uncertainty which can inhibit predictable performance (Benner and Tushman, 2003; Rosenkopf and Mcgrath, 2011). Several academic contributions to the innovation literature have explored this trade-off, stemming from various disciplines and using a number of approaches. Such contributions have included the theories of evolutionary economics (e.g. Schumpeter, 1942), as well as firm-level empirical analysis from the strategic management of innovation (e.g. Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001). A stream of more granular studies further analysed novelty at the inventor or invention level (e.g. Arts and Veugelers, 2014; Fleming, 2001). Some such authors have pointed to distinct processes for firms and inventors so as to better access or encourage novelty, while others have identified various concepts and characteristics of the several aspects of novelty that would contribute to successful and/or radical innovation.

More importantly, the existing studies have highlighted the multifaceted and complex characteristics that govern processes of novelty and its link to value creation. Not all novel inventions are valuable and not every valuable invention is novel (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Whilst the value of novelty can also change depending on the different perspectives of individuals, or which type of skills a firm necessitates at a certain point, the risks and uncertainty are always inherent to the value creation process. Firms should always carefully balance the outcomes of novelty with the potential to incur a certain degree of risks. In general, these distinct characteristics of novelty motivate the need for a better understanding of the processes and the individuals surrounding the generation of novelty.

This doctoral thesis synthesises the multitude of insights, ideas and approaches related to novelty processes. It then goes a step further by deepening empirical research into the technical and social contexts of novelty. It links firm-level processes of knowledge-search, and invention-level *ex-ante* novelty indicators, to consider the value of novelty from a multitude of different perspectives. It explores the value and the risks associated with both technological novelty and firm search processes through distinct novel approaches.

Several researchers denoted that there is no straightforward relationship between economic value and novelty, as not all novel inventions are economically valuable (Strumsky and Lobo, 2015; Verhoeven et al., 2016). As the pursuit of novelty requires resource planning and involves significant risk and uncertainty, a better understanding of the returns gained technological novelty could help firms to employ their resources more efficiently. Despite the large number of studies that analysed the potential benefits and drawbacks, yet a clear view of the processes that associate knowledge-search with the generation of technological novelty, as well as the impact that this link may have on the firm performance has been only marginally analysed (Ahuja and Lampert, 2001; Shane, 2001). This study attempts to move away from the assumption that technological novelty generates from to the exploration of unfamiliar knowledge only and suggests that technological novelty can generates from the exploitation of familiar knowledge as well. Ultimately, a deeper understanding of the interlink between firm generation of technological novelty and the search for new knowledge should provide the tools for firms and practitioners in need of a strategy that lead to the reduction of innovation failures and increased firm's performance.

This thesis thus aims to investigate the following questions:

- What is the real economic value of technologically novelty for the firm?
    - Are firms perceived more valuable when they generate novel inventions?
    - Does technological novelty increase firm's survival?
    - What is the tacit characteristic of breakthrough innovation?

2. Thesis Structure

This thesis seeks to understand the economic risks and benefits that firms may encounter in the search for knowledge and novelty. The first chapter introduces and discusses the existing concepts and indicators of search processes for novelty at both the invention- and firm-level. This chapter reveals the discrepancies between distinct novelty concepts and the existing indicators from two differing levels of analysis. It combines the organisational learning literature with technological novelty and breakthrough innovation literature. The first chapter identifies the gaps in the literature as well as the opportunities for further development. The second chapter offers the value of novelty and knowledge-search processes shed under new light. It examines how they both affect the market value of a firm, based on an investor's expectation of its potential for growth. The third chapter then tackles the risks associated with both novelty and knowledge-search also from a new perspective; analysing their influence on firm failure rates. This aims to increase the awareness of the potential risks involved with the mismanagement of these two important aspects of the innnovation process. This aims to help firms capitalise more efficient expenditure of their resources. The fourth chapter focuses on capturing cognitive novelty by developing a new indicator that uses the textual information in patents. It builds on the premis that novel ideas are basically shifts in existing vocabulary, which aims to further assist in the analysis of breakthorugh inventions. Lastly, the empirical findings from chapter two, three, and four are brought together in the general conclusion section, summarising their combined contribution to the literature. The remainder of this introductionary chapter provides a summary of each chapter, discussing their methods, contribution, implications and, lastly, provides the background theories, the literature review, and the empirical indicators of novelty and search processes.

Chapter I –Introduction (This Chapter)

The literature identifies various forms of novelty from which it has developed several empirical indicators (Arts and Veugelers, 2014; Fleming, 2001; Kaplan and Vakili, 2015; Strumsky and Lobo, 2015). Generally, the literature defines novelty as the basis onto which economically and technologically influential innovation is generated (Rosenkopf and Mcgrath, 2011; Verhoeven, 2016). Since not every radical invention is novel, any attempt to link radical breakthroughs with *ex-post* impact introduces success bias as well as false positive bias (Verhoeven et al., 2016). Thus, for a realistic analysis of the mechanisms behind the process of radical innovation it is essential to consider the role played by novelty.

The first chapter of this thesis aims to put together and describe the distinct search processes that firms generally adopt in order to increase their knowledge and generate novelty. It also decribes the characteristics and origins of novelty itself. This provides an analytical framework that compares the similarities and diffrences of the multiple empirical indicators for patent analysis developed throughout the literature. Moreover, this chapter intends to assist future studies aiming at understanding the variety of aspects of novelty, by serving as a concise and coherent source of information.

Chapter II – Is Exploring Enough, or do You Need to Generate Novelty?

Firm patenting content informs investors about firm's future value (Bessen, 2009; Hall et al., 2000). Prior research found that firms exploring distantly sourced technologies have a higher market value and thus are considered to have greater opportunities for growth (Harrigan et al., 2018). Practitioners must consider investor's expectations as they need access to funding. This encourages the pursuit to understand which type of innovation increases investor's interest. This chapter examines whether it is enough for firms to strategically explore unfamiliar fields, or whether firms must generate novel inventions to encourage investors prospects. Additionally, the analysis will shed light on how investors perceive novelty as either a potential asset for firm growth, or as a signal of uncertainty and potential incumbent risks.

To indicate a firm's inventive prowess, this approach adopts an *ex-ante* measure that indicates the level of novelty in their innovation activity, as well as one that indicates the involvement in a particular kind of search process. *Ex-ante* represent a more rapid source of information regarding firm innovative activity than *ex-post* measures, as these are not immediately available at the time of innovation. Thus, this chapter analyses knowledge-search using a two-dimensional construct which highlights two distinct qualities, namely the exploration of unfamiliar knowledge and the exploitation, or reuse of existing knowledge (Katila and Ahuja, 2002). It also considers novelty as a process of recombination between technological components (Ahuja and Lampert, 2001; Arts and Veugelers, 2014; Fleming, 2001).

Existing research suggests that firms owning patents that cite distantly sourced technologies have higher market value and thus considered to have higher opportunities for growth (Harrigan et al., 2018). However, prior studies failed to consider the orthogonal dimension of the two searh processes, thus provide no evidence of the impact of the exploitation search nor on the symultaneous exploration-exploitation process. This study contributes to the existing literature by showing that investors respond positively to both exploration as well as exploitation knowledge-search process carried out by the firm. Exploration of unfamiliar knowledge is regarded as a better opportunity for growth attracting much more market value than exploiting existing knowledge. Engaging in both search approaches simultaneously is seen as the most promising activity for future value.

In contrast to the existing literature that portrays exploration as a direct link to novel inventions (Ahuja and Lampert, 2001; Levinthal and March, 1981; March, 1991; Rosenkopf and Nerkar, 2001), this study contributes to the organisational learning literature in two ways. Firstly, this study shows a further mechanisms of risk adversity from firm's exploratory search. As the exploratory search is risky and uncertain due to increased innovation failures (D'Este et al., 2018), firm should should adopt mechanisms to reduce risks. This study proposes that firms should engage in the creation of technological novelty whenever they engage in exploratory search. Secondly, this study exposes that exploration does not necessarily lead to novel products. In this study technological novelty is considered as a first-time occurrence of a combination between technological components (i.e. Arts and Veugelers, 2014; Verhoeven et al., 2016) that can generates from either one knowledge-search process. The empirical results demonstrated that exploring is generally perceived as valuable but through the creation of technological novelty exploratory search can signal a winning strategy for the firm's future prosperity.

Chapter III – Recombinant Novelty, Knowledge-Search and Firm Survival

Chapter three aims to shed light on the potential adverse effects of firm innovation by looking at their impact on firm survival. Interestingly, the role of innovation on firm survival has received surprisingly little attention in the literature, and those few studies that do, only look at rudimentary indicators of innovation. Furthermore, most prior studies do not distinguish between distinct exit procedures, which makes it difficult to identify the actual risk associated with the innovation process.

This chapter considers the effect of a firm's knowledge-search process on its mortality rate, as well as other firm-innovation indicators such as the number of patents and their technological novelty. For instance, patents comprising technological novelty have been linked to invention quality measures (Arts and Veugelers, 2014), and are expected to decrease the mortality rate of exit via bankruptcy. However, this may increase the chances of exit through merger and acquisition. In contrast to prior research, this study will control for exit due to failure from exit via merger or acquisition. This construction will allow for the identification of whether the exploitation of familiar knowledge decreases the chances of firm failure, according to the tension view.

This chapter contributes the literature on survival analysis by highlighting the importance of the distinction between exit procedures. Exit of the firm does not necessarily signify business failure. However, business activity can still be competitive when taken over by another firm. In this way not only different impacts of innovation are reported but also distinct firm strategies can be probed. As such, technological novelty may be perceived as a valuable asset by potential acquires leading to a firm eventually exiting via merger and acquisition. By emphasising the role of innovative capabilities in the exit strategies of firms, it will be possible to identify the contribution of the target firms to the merger and acquisition process in terms of the firm's innovation capabilities (Cefis and Marsili, 2012).

Firms pursuing the generation of technological novelty might face substantial risks and uncertainty which may not only lead to lower the overall performance but also potentially contributing to higher chances of firm exiting the market. This study contributes to the technological novelty literature by analysing the trade-off that firms face in the process of generating technological novelty by looking at whether novelty increases the chances of firm's bankruptcy. Furthermore, this study highlights the importance of technological novelty and the existence of synergies with knowledge-search processes in shaping the decision of a firm to exit.

Chapter IV – Knowledge Similarity and Breakthrough Inventions

The lion's share of prior literature has dealt with the technological characteristics of novelty. Yet, a much-neglected aspect of novelty relates to the development of new ideas in the form of novel vocabulary or shift in the existent one (Kuhn, 1962). Only two prior studies examined the link between novelty and semantic dissimilarity (Gerken and Moehrle, 2012), and exposed the link between cognitive novel ideas and higher citation rates (Kaplan and Vakili, 2015). Yet not much is known of the actual cognitive characteristics of breakthrough innovation, which stimulates the need for futher researh.

As such, chapter four focuses on developing two new indicators that will allow the capture of novelty from the text of inventions, and further aim to analyse the distinct cognitive characteristics of breakthrough inventions. The proposed indicators of cognitive novelty identifies a shift in language either from the prior-art citations using a text-matching technique, or from a given patent knowledge area using topic modelling.

The latter indicator detects shifts in knowledge by looking at whether a patent vocabulary is either below or above the average of its assigned topic.

Firstly, this chapter contributes to the literature of breakthrough innovation, as it explores the cognitive aspect of breakthrough inventions using the two proposed indicators. Secondly, this chapter contributes to the literature on technological novelty, as it proposes two cognitive novelty indicators and compares them to existing indicators of technological novelty. Doing this shows that the textual content in patents gives contrasting information provided by indicators using technological classes.

Chapter V – General Conclusion

This chapter presents the overall findings of the thesis, discussing how the initial research question is answered and the gaps of the literature are addressed. Understanding, separating, and capturing the economic impact and the risks of the processes of searching and generating novelty can have significant managerial implications. This could aid firms in better managing their innovative activities and their requirements for the creation of breakthrough innovation. As such, this thesis adds to previous contribution that seems to have only partially looked at the costs and uncertainty associated to the generation of novelty. Furthermore, the economic impact and the risks of knowledge-search focus was analysed, and the most meaningful method identified. Limitations of the studies and ideas for further research are also discussed.

As prior research demonstrated that breakthrough inventions do not generate novel topics thus are not linked to the generation of novel vocabulary (Kaplan and Vakili, 2015). They may instead contribute to an overall shift in popularity of a particular vocabulary from a specific knowledge area. Firtsly, this paper contributes to the literature on technological novelty, as it compares two cognitive novelty indicators to existing technological novelty indicators. Doing this shows the cognitive characteristics of brekathrough innovation and whether this are associated with knowledge-search processes. Furthermore, this study contributes to the extant literature by improving the existing indicators of cognitive novelty, which may be adopted where technological novelty indicators may not be consistent, such as in case of overly broad classes and in moments when patents are only assigned to a single technological class. Furthermore, this paper contributes to the literature of breakthrough innovation by exploring the cognitive aspect of radical inventions. Existing technological novelty indicators are based on the underlying assumption that technological classes reliably reflect components, principles, and fields of knowledge drawn upon to serve the purpose of the technology. However, the use of patent classifications to proxy the technological space may have some biases. The USPTO classifications expose the uneven growth resulting from the first general scheme generated, in which classifications were principally designed to assist patent examiners performing searches . As such, the classification's categories have been created under the subjective assessments of examiners based on their interpretations of the claims and the rules for making classifications (Kaplan and Vakili, 2012). On the other hand, patent documents are rich of informative content and are relatively publicly accessible which makes them the principal choice for the study of innovation activity. This study aims to adopt and construct cognitive novelty indicators to analyse the cognitive characteristics of breakthrough in the biotechnology sector.

The following section outlines the existing firm's processes of knowledge-search from the organisational learning literature, as well as the existing empirical metrics of technological novelty, and finally, it concludes with a few avenues for future research.

3. Several Aspects of Technological Novelty

In the economics of innovation literature, technology is considered as the combination of a set of components that work together in order to fulfil a human need or purpose (Arthur, 2007, 2010; Romer, 2010). These components can be assembled in various combinations and adapted to meet the needs of the task at hand. This is the essence of the *recombinant* characteristic of technology. Innovation scholars advocated that recombination provides the ultimate source of novelty (Gilfilla, 1935; Usher, 1954). Schumpeter (1939, p. 88) stated that:

"innovation combines components in a new way, or that it consists in carrying out New Combinations".

Nelson and Winter (1982, p.130) observed that:

"the creation of any sort of novelty in art, science, or practical life – consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence."

Invention can be either defined as a new combination of technologies or a new relationship between previously combined components (Henderson and Clark, 1990), whereas *Novelty* arises when either new or existing technologies are *recombined* – for the first-time – into an existing collection of technologies (Kogut and Zander, 1992).

The nature of the combination being made can be associated with the search process. Using knowledge and technology in well-understood ways correspond to a search process named exploitation, whereas using knolwedge and technologies in new ways correspond to a search process named exploration (March, 1991). Ultimately, the recombinatory process should provide the potential to generate new and important discoveries (Romer, 1997; Weitzman, 1998).

Invention novelty arises when either new or refined technologies are *recombined* into an existing collection of technologies (Kogut and Zander, 1992). Following this definition, invention novelty integrates distinct technological functionalities and thus it is the direct beneficiary of technological novelty (Strumsky and Lobo, 2015). In other words, technological novelty is the introduction of unprecedented components, whereas invention novelty is a unique and novel device which may not always entail technological novelty but generally encompasses unprecedented assemblies between components

(Hargadon, 1998; Nelson and Winter, 1982; Weitzman, 1998). For example, empirical research identified invention novelty as granted patented, whereas the type of novelty described in the patents claims and/or technological classes as technological novelty.

Novelty is at the heart of the innovative process for the creation of invention, and generally it serves as an essential contributor for the production of high-impact inventions (Arthur, 2010). Many scholars describe novelty as inventions with an exceptional impact, such as further technological improvements, performance, and value (Anderson and Tushman, 1990; Christensen et al., 1996; Henderson, 1990; Rosenkopf and Nerkar, 2001; Utterback, 1994). Such scholars have given novelty a further fine structure describing them as 'radical', 'breakthrough', or 'discontinuous' as opposed to 'run-off-the mill' or "incremental' improvements. Empirical research supported this view exposing that inventions having an exceptional impact typically originate from the recombination of knowledge from a diversity of sources (Trajtenberg et al., 1997), previously extraneous to the field of invention (Dahlin and Behrens, 2005; Shane, 2001). Therefore, *novelty* is also used to define the quality of being unfamiliar, original, and unusual.

The process of creating technological novelty requires significant resources. Firms continuously scan for sources of new knowledge that can increase their potential to generate radical inventions. Some scholars argue that most well-established firms are often too bureaucratic and myopic to offer the type of environment that can develop novel inventions (Dutton and Dewar, 1986; Henderson, 1990; Virany, Beverly; Tushman, 1986). Firms must break away from existing paradigms to develop capabilities for the generation of novel inventions (Nelson and Winter, 1982). A stream of literature following the seminal study by March (1991), argues that firms should balance the exploration of new possibilities with the exploitation of their existing competences; this has been described as 'ambidexterity' (O'Reilly III and Tushman, 2004). As such, several studies started as a direct measurement of the firm focus on either explorative or exploitative capabilities and subsequent invention impact.

Another stream of studies of a more granular kind, focussed on the impact of novelty at the invention and the inventors' levels. Surveys involving managers and industry experts have been used to identify novel aspects of inventions (Acs and Audretsch, 1990; Chandy and Tellis, 2006; Dutton and Dewar, 1986; Laursen and Salter, 2006). Whilst, these methods are mostly used in small studies focusing on a particular kind of invention or area, patent information is usually adopted for assessing macro-scale innovative activities. Some studies have used *ex-post* methods such as the count of citing patents (Carpenter et al., 1981; Gambardella et al., 2008; Browyn Hall et al., 2005), whilst others have employed *ex-ante* measures which rely on references to prior patents or scientific articles. Here one can gauge not only the weight on which preceding knowledge was relied (Banerjee and Cole, 2011; Gittelman and Kogut, 2003; Schoenmakers and Duysters, 2010), but also indicate the uses of technological classifications from their cited references (Dahlin and Behrens, 2005; Nerkar, 2003; Shane, 2001; Trajtenberg et al., 1997). Other scholars looked at the combination of patent assigned technological classes in order to assess the recombination nature of inventions (Arts and Veugelers, 2014; Fleming, 2007, 2001; Strumsky and Lobo, 2015). Furthermore, text mining was used to capture the creation of novel vocabulary as a method for identifying cognitive novel inventions (Kaplan and Vakili, 2015).

Most previous research has drawn from theories of recombination based on the *tension* view of the relationship between knowledge and creativity (Weisberg, 1999). This argues that distantly derived components are essential for the creation of novel ideas that achieve high economic value (Ahuja and Lampert, 2001). In contrast, more recent studies argue that recombining previously used components can also produce novel, economically valuable inventions. Arts and Veugelers, (2014) found that recombining familiar rather than distantly sourced components increases the likelihood of breakthrough innovation. Furthermore, Kaplan and Vakili (2015), found that inventions adopting familiar components are associated with cognitive novel (i.e. inventions that create new vocabulary) and breakthrough inventions. Inventions adopting distantly sourced components, however, are more likely to be breakthrough inventions. Both studies suggest that an effective innovation strategy needs to bridge both distantly sourced and familiar recombination to transform novel inventions into valuables ones. However, since there is no straightforward relationship between economic value and novelty (i.e. not all novel inventions are economically valuable), more research is needed to identify the economic impact of distinct invention novelty types (Strumsky and Lobo, 2015). As the pursuit of novelty requires resource planning and involves significant risk and uncertainty, a better understanding of the returns gained by distinct novelty types could help firms to employ their resources efficiently.

3.1. Ex-ante Indicators of Novelty

A considerable variety of definition and measurement of concepts related to the broad term of 'radical invention' have been developed through the innovation literature. A number of studies have adopted *ex-post* indicators to define radical inventions in terms of the characteristics and their underlying technology. This are often characterised as incorporating technologies that move away from existing practices, embedding novel knowledge, and being based on distinct scientific and enginnering principles compared to existing technology (Verhoeven et al., 2016).

Innovation studies focused on the recombinant characteristic of innovation, emphasised that novelty occurs whenever there is an unprecedented combination of technologies. Technological novelty originates from a first-time combinations between technological components in a specific sector or ever. This was labelled either as a ***New Combination*** (Arts and Veugelers, 2014; Fleming and Sorenson, 2001) or just ***Combination*** (Strumsky and Lobo, 2015), or ***Novelty in Recombination*** (Verhoeven et al., 2016). Technological novelty can also arise from the combination of the previous two, thus the appearance of new knowledge within a new combination, alo labelled as a ***Novel Combination*** (Strumsky and Lobo, 2015). Arts and Veugelers (2014) found that combinations of familiar components are generally less valuable in the biotechnology sector, suggesting that familiarity may still have a negative effect on new combinations (e.g. familiarity trap). On the other hand, novel combinations generate higher citation rates, increase the likelihood of breakthroughs, and are less likely to fail in general. Interestingly, familiarity at high level of recombinant novelty has the strongest impact on breakthrough inventions. Furthermore, Kaplan and Vakili (2015), found that inventions adopting familiar components are associated with cognitive novel (i.e. inventions that create new vocabulary) and breakthrough inventions. Strumsky and Lobo (2015) found that *novel combinations*, inventions including both brand new component and combinations, are associated with higher citation rates, and receive the highest number of citations when compared to other novelty types.

Novelty can also occur whenever there is the appearance of an new technology or an ***Origination***, which is the occurrence of brand-new knowledge in the form an unprecedented technolgy. The introduction of first-time occurrence components certainly reflects technological development, but it does not have a relevant effect on highly cited inventions (Strumsky and Lobo, 2015). However, the beneficial effect of firms generating an origination (i.e. a patent with only first-time occurrence technological classes) might ripple down to subsequent inventions, and thus create the opportunity for later breakthroughs. Arts and Veugelers (2014) further revealed that those inventions including first-time appearance technologies (i.e. novel *components*) apparently do not contribute to breakthrough. Interestingly, Ahuja and Lampert (2001) firm-level analysis demonstrates that introducing novel components affects the likelihood of a breakthrough.

Verhoeven et al. (2016) take the construction of technological novelty a step further by considering the first-time combination of at least two cited prior art inventions, and label this as an invention comprising ***Novel Technology Origin***. Thus, a novel invention is considered a novelty in technology origin when it comprises at least one unprecedented combination of prior-art citations. Moreover, an invention can also be characterised by ***Novel Scientific Origin,*** *which occurs* whenever an invention comprises a first-time combination of at least two cited prior art scientific papers. Verhoeven et al. (2016) shows that inventions comprising all three novelty types (e.g. novelty in recombination, novelty in scientific knowledge, and novelty in technological origins) are the most powerful source of breakthrough innovation. Interestingly, *recombinant novelty* is the most significant contributor to breakthrough inventions, whereas both *novelty in recombination* (i.e. *novel combination*) and *novelty in technological origins* highly affect the chances of winning an R&D award. On the other hand, drawing knowledge from scientific domain seems to produce breakthroughs only at a high recombinant novelty or technological origin novelty, whereas it does not show to impact significantly the likelihood of winning an R&D award (i.e. although this is might be due to its variable's overly skewed characteristic).

Novelty identified through patent citation analysis involves some drawbacks such as, the scope of information is limited as the description of the invention is ignored (Lee et al., 2009), and the strategic referencing bias cannot be avoided as patent owners can also strategically cite their own patents. To overcome these limitations alternative approaches that focus on the analyses of the patent text and keywords were developed. These methods involve a comparison of the occurrence of keywords in patents (Li et al., 2009), or extracting and classifying keyword (Yoon and Park, 2004). Furthermore, other methods were developed to incorporate the functional relationship of an invention. These approaches are based on the Subject-Action-Object-structures (SAO), can clearly show the structural properties of inventions (Yoon and Kim, 2012). Gerken and Moehrle (2012) identified ***Semantic Novelty*** as patent the proportion of semantic structure diversity from a patent backward citation. The text mining approach carried out by Gerken and Moehrle (2012) demonstrated that semantic patent analysis outperforms overlapping similarity (Dahlin and Behrens, 2005) and technological distance (Hall et al., 2005) in identifying highly novel inventions in the automotive industry. Further advancement in text mining analysis by Kaplan and Vakili (2015) attempted to separate between the ***Cognitive Novelty*** (i.e. in the Kunian sense of introducing new vocabulary) and *economic* impact of potential breakthroughs, using topic modelling. Kaplan and Vakili (2015) found that most of the patents considered breakthroughs in value are not cognitively novel and thus do not provide new knowledge. As such, breakthroughs are product of the recombination process of already existent technologies. The exploitation of familiar components into narrow recombinations seems to provide higher cognitive novelty which has also been linked to subsequently increase the likelihood of breakthrough inventions. On the other hand, distant and diverse recombination provides less cognitive novel inventions but higher likelihood of breakthrough. This peculiar behaviour is the "*double edge sword of recombination"*.

Table 1 Ex-Ante Measures of Invention Novelty

N.	Indicator	Concept	Operationalisation
1	*New Combinations*	Novelty generated by the introduction of first-time combination of components	A patent number of unprecedented subclass pairs (from the whole USPTO) divided by the patent's total number of subclass pairs, resulting in a measure between zero and one (Fleming and Sorenson, 2007; Arts and Veugelers, 2014; Strumsky and Lobo, 2015)
2	*Origination*	Novelty generated by completely new knowledge (components)	A patent having only new classes (Strumsky and Lobo, 2015)
3	*Novel Combination*	Novelty generated by at least a novel combination and including the introduction of new knowledge (new component)	A patent having new combinations with at least one new class (Strumsky and Lobo, 2015)
4	*Novel Technology Origin*	Novelty generated by the first-time combination of two cited prior art inventions	A patent number of new backward citations combinations (Verhoeven, Bakker, Veugelers, 2016)
5	*Novel Scientific Origin*	Novelty generated by the first-time combination of two cited prior art scientific papers	A patent number of new backward citations combinations to scientific papers (Verhoeven, Bakker, Veugelers, 2016)
6	*Cognitive Novelty*	Novel ideas in the form of the introduction of novel vocabulary	A patent introducing a new concept which defines a novel topic using topic modelling (Kaplan and Vakili, 2015)
7	*Semantic Novelty*	The proportion of semantic structure diversity from a patent backward citation	One minus the maximum similarity to its preceding patents (Gerken and Moehrle, 2012)

Adjacent empirical studies focused on the analysis of the characteristics of radical innovation, constructed a variety of indicators based on the *tension* view of the relationship between knowledge and creativity (Weisberg, 1999). The tension view argues that distantly derived components are essential for the creation of novel ideas that achieve high economic value (Ahuja and Lampert, 2001). Following this perspective, when a patent cites patents in classes other than the one it is in, this suggests that the patent builds upon technological paradigms different from its application. In this sense novelty is based on the assumption that the more distant and diverse knowledge which an innovation draws upon leads to greater potential for recombination. Moreover, the empirical literature suggests that the more technological components have been used by previous inventions the more inventors learn about successful and unsuccessful applications and the better their foresight in how to use this components in different ways and contexts (Cohen and Levinthal, 1990; Hargadon, 2003).

For example, ***Technological Distance*** is the measure that indicates the degree of distantly sourced technology of a focal invention from the prior-art knowledge it draws upon (Caviggioli, 2016; Kaplan and Vakili, 2015; Trajtenberg et al., 1997). Whereas, ***Technological Diversity*** identifies the breadth of the prior-art's knowledge from which a focal invention draws upon (Hall et al., 2005; Kaplan and Vakili, 2015). Fleming (2001) and later Kaplan and Vakili (2015) found that more distant and diverse combinations are linked with useful inventions on average, whereas impact on breakthroughs is positive but not statistically significant. Furthermore, adjacent studies revealed an insignificant association to invention's quality (e.g. R&D prize winning) (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Similarly, the *spread of sourcing* or **Originality** (Trajtenberg et al., 1997), which indicates inventions characterised by 'synthesis of divergent ideas', has a significant negative impact on the likelihood of breakthrough, indicating a narrow focus of the highest cited patents. Adopting a more diverse knowledge sourcing strategy might not necessarily lead to novel approaches, for example in those fields in which is usually normal to source from other fields.

Another indicator of technological boundary spanning is *external sourcing* or ***Radicalness***[1], developed by Shane (2001) and Briggs and Buehler (2018) indicates the

[1] It is important to mention that the Radicalness measure described here is different from the one in Dahlin and Behrens (2005). The radicalness described by their study refers to a broader definition radical

degree to which innovation draws knowledge from other fields than its own. Similarly, sourcing outside one's own technology area may be a characteristic which novel inventions are more likely to display, but it does not identify them. Citing prior-art from other knowledge areas is not a sufficient condition to actually introduce a novel approach since there might have been several previous inventions might have already sourced knowledge from those knowledge areas before. Briggs and Buehler (2018) results suggest an inverted U-shape relationship, as radicalness initially increases the likelihood of breakthrough innovation until the point where too much radicalness has the opposite effect.

The ***Overlap Score*** identifies the degree of dissimilarity and uniqueness of citation structure with respect to prior-art citations with respect ot all other inventions filed in the same year, as the yearly average overlapping between the backward citations of each patent granted with all other granted patents in the same field. Those patents that have low overlapping scores compared to prior art in the field are considered more inventive and unusual. Those inventions without backward citations have the lowest possible overlap score and are considered more radical or ground-breaking (Ahuja and Lampert, 2001). Arts et al., (2013) study shows that radical inventions in the biotechnology sector, cite more inventions and have dissimilar backward citations compared to prior-art in the same field but do not rely on prior-art from a broader range of technology fields.

In general the extant literature suggests that an effective innovation strategy needs to bridge both distantly sourced and familiar recombination to transform novel inventions into valuables ones. Keijl et al. (2016) identified as ***Distant Recombinations*** those inventions that substantially differ from their technological origins. The greater the average distance between the components of the prior-art inventions and the focal invention the greater the potential for recombination. This concept not only considers the number of domains, but it emphasises the role of distance between domains. The study identifies three technological distances (e.g. *near, adjacent, distant*) between the focal and the prior-art inventions components. The results demonstrated that an intermediate level of recombination provides the highest impact on innovation.

invention which comprises three fundamental characteristics including novelty, uniqueness and impact on future technology.

Table 2: Other Ex-Ante Measures of Technology Distance and Diversity

N.	Indicator	Concept	Operationalisation
1	*Overlap Score (Uniqueness)*	How unique is the citation structure with respect to patents granted in the focal patent's same year	The overlap scores between the backward citations of each patent P granted in year t with all other granted patents1 in the same field, and averaging these overlap scores within each year relative to the grant year t. (Dahlin and Behrens, 2005; Arts et al, 2013)
2	*Overlap Score (Dissimilarity)*	How dissimilar the backward citation structure is with respect to prior art.	The overlap scores between the backward citations of each patent P granted in year t with all other granted patents1 in the same field, and averaging these overlap scores within each year relative to the grant year t. (Dahlin and Behrens, 2005; Arts et al, 2013)
3	*Technological Breadth*	Technological class heterogeneity of a citing patent	A patent number of unique technological classes (Schoenmark and Duysters, 2010, Kelley et al., 2013, Arts and Veugelers, 2014)
4	*Originality*	Herfindahl index on technological classes of citing patents	A patent backward citations' spread of technological fields measured as, the sum of the squared number of different citations in each distinct class divided by the total number of citations. (Trajtenberg et al, 1997)
5	*Technological distance*	The technological difference between prior art and the focal invention technological components	Dummies equal to one when the merged technical fields have respectively different IPC sections (first digit), IPC classes (3-digit code), wipoconc areas (5 categories) or fields (35 categories), each multiplied by an elasticity measure (w) (Trajtenberg et al, 1997; Kaplan and Vakili, 2015; Caviggioli, 2016)
6	*Technological diversity*	The degree of technological heterogeneity of the prior art on which an invention builds upon	One minus the Herfindahl index of the concentration of the USPTO patent classes in the previous art cited by a focal patent (Hall et al, 2001, Kaplan and Vakili, 2015)
7	*Knowledge flow (Far External - External - Near - Others)*	The degree of distance of the knowledge used to generate inventions	Distance between a focal patent technological component and the backward citations components (a pair is considered internal if both patent i and the cited patent are in the same class. If they are in different classes, they are considered an external pair. The pair is coded as near if the pair share the same sub-class. The pair is coded as far external if the two are in different super-classes.) (Nemet and Johnson, 2012)
8	*Radicalness*	The degree to which an invention sources in knowledge from outside its own field	The index divides the number of unique classes embodied in a patent's backward citations that are not embodied in the patent, divided by the total number of classes contained in a patent's backward citations (Shane, 2001; Verhoeven et al, 2016; Briggs and Buehler, 2018)
9	*Distant Recombination (near – adjacent – distant)*	Novel combinations between distant components	A patent sum of technological classes distances between bcs and the focal patent (near citation is weighted with 1, an adjacent citation is weighted with 2, and a distant citation is weighted with 3), divided by the number of bcs (Keijl, et al., 2016)

On the other hand, technological distance and diversity were found to be unrelated to the indicators of technological novelty (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Interestingly, inventions embodying a combination of distinct novelty types, such as novelty in both combination and components, were found to be more successful on average than sourcing distant and diverse knowledge (Strumsky and Lobo, 2015; Uzzi et al., 2013; Verhoeven et al., 2016). Lastly, a few studies demonstrated that innovation from familiar technological components and novel combinations generate more highly cited inventions on average than those inventions comprising distantly sourced components (Arts and Veugelers, 2014; Fleming, 2001; Kaplan and Vakili, 2015). This further suggests that having a deep understanding of a specific domain and the ability to recombine familiar technologies together are essential for developing impactful ideas.

4. Sources of Technological Novelty

4.1. Firm's Exploratory vs. Exploitative Knowledge-Search

In the organisational learning literature two distinct and sometime contraposing *knowledge search strategies* were of central concern, the *exploration* of new possibilities and the *exploitation* of old certainties (Holland, 1975; Kuran, 1988; March, 1991; Schumpeter and Opie, 1934). Both exploration and exploitation are essential for firms, but firms have to carefully choose to allocate typically limited resources. It can be complicated for firms to make choices in balancing between exploration and exploitation, particularly when considering the substantial difference in values of returns from the two options. Therefore, several studies adempted to analyse the characteristics of firms' knowledge search strategies and their related outcomes to inform and guide firms through the strategic innovation process.

A fundamental goal for a firm in the position to choose a specific strategic search process is to innovate through the generation of novel ideas and technologies. Firms must create new unprecedented inventions with unique *and* novel characteristics. To do so firms must search for new resources and knowledge that will allow them to either create novel inventions or combine previous ones. Several researchers, with an evolutionary perspective, regarded *technological novelty* as a *recombinant* process. Accordingly, inventions are the product of a combination of existing technologies into new synthesis (Ahuja and Lampert, 2001; Fleming, 2001; Henderson and Clark, 1990; Kogut and Zander, 1992; Tushman and Rosenkopf, 1992). Thus, firms which then combine their own ideas into existing ideas eventually produce patentable inventions, which serve as knowledge for future inventions (Fleming, 2001). Other researchers emphasised the importance of *variety* in the innovative process (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Lazonick, 2005; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008). The higher the variety, the higher the knowledge for innovation.

According to Katila and Ahuja (2002), distantly sourced knowledge-search enriches the knowledge pool by adding distinctive new variations. Novel variations are essential to firms for the creation of a sufficient amount of choice in solving problems (March, 1991). In other words, an increase in scope adds new elements to the set, improving the possibilities for finding a new useful combination (Fleming and Sorenson, 2001; Nelson and Winter, 1982). Furthermore, firms engaging in only local and familiar knowledge might lead to myopic behaviour and cognitive biases (Levinthal and March, 1993; March, 1991); an exploratory search can help firms overcome these problems (Ahuja and Lampert, 2001). Therefore, the exploratory search is a search behaviour that involves a conscious effort to move away from current organisation routines and knowledge bases (Katila and Ahuja, 2002).

Several prominent researchers argued that firms should engage in distant and diverse research to innovate and demonstrated that exploring rather than exploiting creates a higher likelihood of breakthrough inventions as well as product innovation (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001). Through the empirical studies, some researchers treat explorative and exploitative search as a continuum within which a balance can be achieved; other researchers describe search processes as orthogonal, in which both exploration and exploitation coexists within a firm (Lavie et al., 2010). Firms simultaneously involved in the two processes were described as “ambidextrous” (O’Reilly III and Tushman, 2004).

From the assumption that the exploration process can be uncertain and risky for the firm that pursue it, and this was referred to as the “*vulnerability of exploration”* (March, 1991), a second strand of literature suggested that firms should engage with the exploitation rather than the exploration search process. Further theoretical studies advanced this concept through considering the complexity of the technological problem-solving activities. Two important points were described: firstly the limited cognitive abilities of employees would restrict the solution of problems to a limited number of solutions, which the majority could be within their knowledge spectrum (Knudsen and Levinthal, 2007). Secondly, as more knowledge of a specific scientific field is accumulated, the easier the learning related to that knowledge (Constant II, 1980; Laursen, 2012; Vincenti, 1990). Therefore, it is naturally to think that the employees of a firm initially search for solutions in areas where the firm has already expertise. As described by (Cohen and Levinthal, 1990), proximate and familiar knowledge should be easier to learn than distant and unfamiliar one.

According to March (1991) exploitative search can have potential drawbacks for the firm that become too reliant on this type of search. A potential problem may occur when a problem can only be solved with external knowledge. Thus, sometimes local search can lack inspiration and variety required for problem solving (Postrel, 2002). Moreover, the frequent use of the same knowledge can lead to myopic behaviour and cognitive biases (Levinthal and March, 1993). As shown by Laursen (2012) the initial trend among scholars was to show the theoretical and empirical impact of local search, whereas more recent contributions focused on understanding why firms tend to predominantly search locally and how can they balance exploratory search and avoid the *familiarity trap*. Although, several studies have attempted to answer these questions research has yet to demonstrate how this balance can be achieved.

4.2. Continuous vs. Orthogonal Knowledge-Search

From the disagreeing results on the role of exploration and exploitation research focus, it should be sensible to suggest that an appropriate balance between the two research focuses should be the optimal choice for firms' survival and propensity. A few studies considered a firm's novelty level to be a continuous inverted-U shaped curve in relation to firm's performance. However, the operationalisation of the level of exploration-exploitation varies among prior studies. Lavie et al. (2010) theorise a conflict-type behaviour by measuring relative levels of each behaviour. Other studies instead, start from the assumption that successful organisations do attempt to simultaneously engage in both exploration and exploitation at the same time, depending on the objectives of separated organisational units (Benner and Tushman, 2003; O'Reilly III and Tushman, 2004) or even through processes (Mom et al., 2009). This latter approach visualises exploration-exploitation balance in an orthogonal relationship and it was referred to as firms or managers' capacity to ambidexterity. For example, Cao et al., (2009) shows that firms in resource-rich environments should focus on both exploration and exploitation at the same time, whilst those firms that are resource constrained benefits from advancing one focus more than the other. The optimal ratio between the two research focuses depends heavily on the industrial context and the firm specific set of practices to another (Rosenkopf and Mcgrath, 2011).

Rosenkopf and Mcgrath (2011) provide an extensive overview of the survey-based studies on the exploration-exploitation arena. The study shows that there is both theoretical and operational methodological dissonance. Moreover, differences such as private versus public firms were not taken into account, further decreasing the possibility of direct comparison as well as their generalisability potential. Further discrepancies are displayed in *large-sample archival* studies as they suggest divergent results by taking into account different contexts in which exploration-exploitation is considered. Lavie and Rosenkopf (2006) empirically demonstrated to obtain different results when taking into account exploration from different contexts (e.g. structural domain vs. functional domain exploratory focus), suggesting that different types of explorations could be additive. However, this relationship was later suggested to be a in the form of a balance within each context (Lavie et al., 2011), assumed to be dictated by the costs of managing resources conflicts as well as developing routines.

Rosenkopf and Mcgrath (2011) observed that studies on exploitation-exploration consider *novelty* as distinct types of *mechanisms* of exposure to new knowledge (i.e. any activities such as learning, innovation, and other strategic behaviour), and their *contextualised position* of the activity. Mechanisms previously studied included alliance formation (Beckman et al., 2004a; Rothaermel and Deeds, 2004) patents resulting from internal R&D (Benner and Tushman, 2003; Sorensen and Stuart, 2000), acquisitions (Puranam et al., 2006; Vermeulen and Barkema, 2001), and mobility (Groysberg and Lee, 2009; Rosenkopf and Almeida, 2003), or new product development (Danneels, 2002; Katila and Chen, 2008). Based on which application of mechanism these studies focus on, the novelty of these mechanisms can be classified based on their contextualised positions by which the mechanism can be compared with past activity to assess novelty or familiarity.

4.3. Social and Technical Contexts of Knowledge-Search

Prior research identified and categorised two types of novelty contexts embedded in the organisational learning processes. Innovation novelty is captured by the *technical* context whereas inter-intra-organisational relationship is captured by *social* context. Part of the technical context has been examined through the patent portfolio of the firm. A patent is the building block on which a firm’s product or service is constructed, and the quality of the patent can assess whether it contributes substantially to the extension of existing knowledge (i.e. incremental innovation) or it creates a novel and radical shift from the current field (i.e. radical innovation). This valuation was performed in various ways. Ahuja and Lampert (2001) consider *technological novelty* as a firm was considered to have entered a new technology class when it first applies for a patent in a class in which it was not familiar with in the previous 4 years. Arts and Veugelers (2014) consider *recombinant novelty* as the patents level of new unprecedent combination of subclasses.

Part of the studies focusing on the social context, consider novelty as the firms' organisational boundary. Rosenkopf and Nerkar (2001) takes into account the patent citations from the patenting firm against other firm implying that knowledge coming from the firm itself is familiar whereas knowledge from other firms would be considered more novel. Another set of studies focused on the social contexts of the geographic space, in which local search is seen as familiar whilst distant search as unfamiliar. According to Rosenkopf and Almeida (2003) firms' alliances and mobility to distant regions provide higher chances to exposure to diverse knowledge other than the redundant technological know-how. Singh (2005) empirically demonstrated that regional and firm boundaries restrict knowledge diffusion and distance strengthen network collaborations.

Phene et al. (2006) uses a more complex approach to novelty which considers different combinations of technological and geographic contexts simultaneously. Although specific to the biotechnology industry, the study reveals that firms' sourcing local (i.e. national) technologically distant knowledge has a curvilinear effect on breakthroughs whilst sourcing international knowledge which is technologically familiar has a positive impact on breakthrough innovation. To further extend the literature of social contexts, a few studies considered alliances formation decisions as a further context and partners' relationships as the learning activity and assess their development in comparison to pre-existing relationships. This approach assumes that firms entering new partnerships with repeated partners are less novel than first-time partnerships (Beckman et al., 2004a; Kogut and Zander, 1992; Rosenkopf and Mcgrath, 2011).

5. Existing Indicators of Knowledge-Search

5.1. Indicators of Firm's Knowledge-Search Focus

From Table 3, several indicators of invention novelty were constructed throughout the empirical studies that focused on knowledge-search focus of the firm. The indicators constructed were based on several sources through which a firms can spur novelty, including searching *locally*, (2) exploration both inside the technological domain and the organisational boundaries; *radically,* (3) exploration both outside the technological domain and the organisational boundaries, *internally*, (4) exploration inside the firm's knowledge-boundary domain, *externally*, (5) exploration outside the firm's knowledge-boundary domain (Rosenkopf and Nerkar, 2001). According to Katila and Ahuja (2002), firms can use and reconfigure their existing knowledge repeatedly leading to varying degrees of familiarity. A firm can thus increase its novelty through searching *deeply*, (6) the intensity of reusing a firm's *familiar* knowledge, and *widely*, (7) the intensity of a firm's introducing *unfamiliar* knowledge. As Laursen, (2012) pointed out this operationalisation refers only to the fact that search domain is new to the firm, but it may be within the same technological area that the focal firm is normally engaged in. (Laursen and Salter, 2006) built on this two-dimensional representation of a firm's strategic search focus by considering whether depth and scope are sourced external to the firm's technological and organisational boundaries. Thus, firms can increase novelty through searching *deeply externally,* (8) the extent to which firms draw intensively from different search channels or sources of innovative ideas, and *widely externally*, (9) the extent to which a firm draws knowledge from external sources. Finally, (Ahuja and Lampert, 2001) consider a firm generation of novelty through introducing *novel components*, which is the introduction a new unprecedented component technology to the firm set of technologies.

5.2. Empirical Evidence of Firm's Knowledge-Search

The exploitation process is important for the fine-tuning and the economisation of the efficiency of the existing technology (Levinthal and March, 1981). (Katila and Ahuja, 2002) demonstrated that exploitation can also increase new knowledge, through new combinations of existing solutions (Schumpeter and Opie, 1934). The distinct knowledge search lead to variations in firms' performance. Katila and Ahuja (2002) suggests that search is most likely to be fruitful when it uses both familiar and unfamiliar elements, as the firm that combines the two searches together has a positive effect on product innovation. The study found that *search depth* has an inverted U-shape curvilinear relationship with new product innovation. *Search scope* was found to have a positive linear relationship with product innovation. Search depth seems to have a greater impact than search scope by a factor of three, which is in line with the proposition that firms tend to search locally with the primary objective of decreasing uncertainty (Helfat, 1994; Stuart and Podolny, 1996). Similarly, Cohen and Caner (2016), using the same measures of Katila and Ahuja (2002) study, demonstrated that exploitation produces novel ideas that survive more frequently than exploration, as exploitation makes a stronger contribution to breakthrough invention than exploration.

Table 3: Measures of Firms Search Focus

N.	Indicator	Concept	Operationalisation
1	*Components novelty*	Novelty generated by a firm adopting new knowledge (components)	A firm generating a patent with at least a new IPC class (Ahuja and Lampert, 2001)
2	*Local*	Exploration both inside the technological domain and the organisational boundaries	A firm yearly number of patents citations that are within the technological domain and filed by the focal firm. (Rosenkopf and Nerkar, 2001)
3	*Radical*	Exploration both outside the technological domain and the organisational boundaries	A firm yearly number of patents citation that are from outside the firm technological domain and are filed by other firms (Rosenkopf and Nerkar, 2001)
4	*Internal Boundary Spanning*	Exploration inside the firm's knowledge-boundary domain	A firm yearly number of patents citation that are from outside the firm technological domain and are filed by the focal firm (Rosenkopf and Nerkar, 2001)
5	*External Boundary Spanning*	Exploration outside the firm's knowledge-boundary domain	A firm yearly number of patents citation that are from inside the firm technological domain and are filed by other firms (Rosenkopf and Nerkar, 2001)
6	*Depth*	Degree of familiarity, how intensely a firm reuses its existing knowledge	Search depth is measured by the 'number of times a firm repeatedly used the citations in the patents it applied for' (Katila and Ahuja, 2002). The average of all citations, number of times the repeated citations were used in the previous five years.
7	*Scope*	Degree of novelty, how widely the firm explores new knowledge	Search scope is measured as 'share of citations found in a focal year's citations that could not be found in the previous five years' list of patents and citations by the firm (Katila and Ahuja, 2002). The proportion of previously unused citations, in the previous five years, in a firm's focal year number of citations.
8	*External Search Depth*	The extent to which firms draw intensively from different search channels or sources of innovative ideas.	A number between 0 and 16, adding up 1 when the firm in question reports that it uses the source to a high degree and 0 in the case of no, low, or medium use of the given source. (Laursen and Salter, 2006)
9	*External Search Breadth*	The extent to which a firm draws knowledge from external sources	A number between 0 and 16, from the combination of the 16 sources of knowledge or information for innovation. The higher the number the higher the breadth. (Laursen and Salter, 2006)

A few more studies emphasised other positive characteristics of firms' exploratory search, including increased in re-combinatory potential, and increases in innovation performance outcome. Ahuja and Lampert (2001) found that introducing first-time appearance technologies in an invention (i.e. novel *combination*) enables firms to overcome the familiarity trap and to produce breakthroughs in an inverted U-shape. (Rosenkopf and Nerkar, 2001) study exposes that exploration beyond organisational boundaries obtains persistently more impact than exploration within organisational boundaries. On the other hand, firms that focus on core competences are more likely to produce marginal innovation. In particular, the study suggests that firms should focus on exploration beyond organisational boundaries, but within the firm's technologically familiar boundaries (e.g. *external boundary spanning*). External boundary spanning produces a positive significant effect on narrow domain impact, which is future citations having equal technological class to the focal invention, whereas, internal boundary spanning provides a negative effect on narrow domain impact. Interestingly, local exploration seems to significantly lower the effect on the overall impact, which is future citations having many different technological classes to the focal invention, whilst radical exploration gives significant positive effect on overall impact.

Laursen and Salter (2006) demonstrated that firm's searching widely and deeply across a variety of search channels should generate ideas and resources that increase the innovative opportunities, however, too much explorative search decreases a firm's innovative performance. Furthermore, external search depth is associated with radical innovation. Innovative firms need to acquire knowledge form a restricted range of external sources including lead users, component suppliers, and universities. Innovators need to draw deeply from their knowledge and experiences in the early stages of product development. Afterwards, the number of potential sources supporting innovation grows along with the technology and the market expansion. Therefore, firms look through a number of search channels to access variety of knowledge that will allow new combinations of existing technologies and ultimately improve their existing products.

5.3. Indicators of Technological Novelty & Familiarity

Many empirical measures have been developed alongside the variety of concepts related to technological novelty. Surveys involving managers and industry experts have been used to identify novel aspects of inventions (Acs and Audretsch, 1990; Chandy and Tellis, 2006; Dutton and Dewar, 1986; Laursen and Salter, 2006). Whilst, these methods are mostly used in small studies focusing on a particular kind of invention or area, patent information is usually adopted for assessing macro-scale innovative activities. Some studies have used *ex-post* methods such as the count of citing patents (Carpenter et al., 1981; Gambardella et al., 2008; Bronwyn Hall et al., 2005), whilst others have employed *ex-ante* measures which rely on references to prior patents or scientific articles. Here one can gauge not only the weight on which preceding knowledge was relied (Banerjee and Cole, 2011; Gittelman and Kogut, 2003; Schoenmakers and Duysters, 2010), but also indicate the uses of technological classifications from their cited references (Dahlin and Behrens, 2005; Nerkar, 2003; Shane, 2001; Trajtenberg et al., 1997). Other scholars looked at the combination of patent assigned technological classes in order to assess the recombination nature of inventions (Fleming, 2007, 2001; Strumsky and Lobo, 2015). Furthermore, text mining was used to capture the creation of novel vocabulary as a method for identifying cognitive novel inventions (Kaplan and Vakili, 2015).

Chapter II

IS EXPLORING ENOUGH, OR DO YOU NEED TO GENERATE NOVELTY?

1. Introduction

The search for new ideas is a process which involves a considerable amount of time, money, and resources. Firms must *search* for new ideas to increase their knowledge, which in turn increases the potential to generate inventions, and potentially spur on technological breakthroughs. Knowledge-search is the process that firms use to develop new solutions and technological ideas whilst undertaking a problem-solving activity. Here, new technologies are combined with the aim of creating novel products (Katila, 2002). Firms develop distinct knowledge-search strategies which may include employing internal know-how as well as capturing external knowledge for the development of new technologies. External knowledge can be accessed through assimilating information from existing knowledge bases (e.g. patents, scientific publications) and/or by working closely with external partners (Laursen and Salter, 2006).

Engagement in innovation activity indicates a firm's strategic capabilities and future earning potential. Patenting, for example, represents a firm's ability to create new or improved products (Bessen, 2009; Hall et al., 2000). Furthermore, firms owning highly cited patents experience higher market volatility (Mazzucato and Tancioni, 2012), and firms owning patents citing distantly sourced technologies have a positive impact on their market value (Harrigan et al., 2018). This seems to suggest that firms are perceived as valuable not only in moments of positive outcome generation but indicates that a firm-specific organisational learning strategy may also be perceived as valuable as it may eventually lead to higher growth opportunities. For instance, *ex-ante* patent measures can show whether patents build upon local or more distant knowledge, thus indicating to some degree, the embedded novelty of innovation. However, the explorative knowledge-search involves considerable risk and uncertainty which gives rise to concerns regarding realistic positive outcomes. Therefore, are investors aware of the potential side-effects of intense focus on a particular knowledge-search strategy? Do investors value firms that are 'ambidextrous'?

This study has two aims. The first aim is to identify whether firms focus on exploring new fields or exploiting their existing knowledge base, in the hope of increasing a firm's innovation quality, and as to whether intense knowledge-search processes can eventually increase the likelihood of invention failures. The second aim seeks to identify whether firms should generate novelty or whether only the exploration of unfamiliar knowledge should be enough to increase investors optimism regarding the firm's potential value. This is investigated by looking at the impact of a firm's patent novelty and knowledge-search processes on the market value, or 'Tobin's q ratio', which is a reflection of the investors' expectations of a firm's prosperity. This study will use a two-dimensional construct of knowledge search, in line with the theory that firms' search varies in two distinct dimensions. Firms can reuse their existing knowledge just as they can vary in their exploration of new knowledge (Katila and Ahuja, 2002).

The remainder of this paper proceeds as follows. In Section 2 briefly summarises the findings from prior studies from the organisational learning literature are briefly summarised. Section 3 contains a short description of the dataset used for the analysis which combines financial data and patent data for 647 firms from the ICT sector and 4,784 firm-year observations between 1999 and 2006. In Section 4, results are presented from the multivariate generalised least squares and the probit models for the analysis of the effect of knowledge-search on firm's stock of weighted patent citations and innovation failures. Furthermore, this section includes the results from the generalised estimated equation model on the effect of knowledge-search on firm's Tobin's q ratio. Finally, Section 5 concludes and offers some implications for the findings.

2. Conceptual Background

2.1. Exploration vs. Exploitation Knowledge-search

March and Simon (1958) and Nelson and Winter (1982) defined *local search* as the nature of individuals and firms to seek knowledge within the boundaries of its current expertise or understanding (Stuart and Podolny, 1996). Innovation studies brought empirical evidence of firms' tendencies towards local search, through R&D spending (Helfat, 1994), product design (Martin and Mitchell, 1998), and trends in patenting activity (Stuart and Podolny, 1996). By focusing on local search, firms increase the propensity to produce incremental inventions, thereby building competences that enables them to accumulate expertise, eventually resulting in beneficial competitive advantage. Search processes are almost always highly localised in that firms search along established trajectories shaped by past experience, routines, and heuristics (Cyert and March, 1963; Dosi, 1982; Malerba, 1992; Nelson, 1991; Nelson and Winter, 1982). As Nelson and Winter (1982) described, organisations are usually better off at self-maintenance tasks in a constant environment, than at major changes. They would be much better at doing “more of the same” than they are at change. In other words, learning is easier if it is restricted to familiar and proximate neighbourhoods (Cohen and Levinthal, 1990).

Further studies stressed that firms tend to predominantly search locally due to the complexity of problem-solving in technology research. There are two principle reasons for the strategy. Firstly, the limited cognitive abilities of employees restricts the number of potential solutions, the majority of which could already be within their knowledge spectrum (Knudsen and Levinthal, 2007). Secondly, the more knowledge of a specific scientific field is accumulated, the easier the learning related to that knowledge (Constant II, 1980; Vincenti, 1990). Accordingly, a common trait of a firm’s employees’ behaviour initially is to search for solutions in areas where the firm already has expertise. As further described by Cohen and Levinthal (1990), proximate and familiar knowledge should be easier to learn compared to distant and unfamiliar knowledge.

Increases in product innovation are linked to increased exploitation through three kinds of experience effects, including: reduction of errors, failures, research time, and consequently costs (Katila and Ahuja, 2002). First, the repeated use of similar components facilitates the development of routines making the search more reliable whilst reducing the likelihood of errors (Levinthal and March, 1981). Experienced researchers will move more confidently through familiar areas of knowledge, decreasing the time to produce novel discoveries. Secondly, familiarity also increases the researchers’ understanding of product requirements which have to be met, so that they are able to split and reorder activities efficiently into solvable sub-problems, eventually eliminating unnecessary steps. Thirdly and finally, the repeated usage and deeper understanding of concepts increases a researchers’ ability to identify the valuable components in their products. Researchers may leverage the value by focusing on the advancement of the important component, and their combination in varied and significant ways. In addition, because agents develop an understanding of ‘local’ elements which could potentially be combined, they are better able to invent, and with greater reliability by avoiding elements that did not work in the past (Fleming and Sorenson, 2004; Vincenti, 1990).

Excessive exploitation by a firm may lead to negative consequences including: firm’s rigidity, limits to exploitation of a technological trajectory, and resistance to communication across knowledge boundaries (Argyris and Schön, 1997; Carlile, 2002; Dosi, 1988). Eventually, these problems lead to diminishing returns, a decrease in product output leading to the costs of depth exceeding its benefits. For instance, Katila and Ahuja (2002) demonstrated that an intensive focus on exploitation is disadvantageous, as this creates an inverted U-shape relationship with firm's market product introduction. Several other researchers argued that excessive local search may lead firms to develop core rigidities (Dororthy Leonard-Barton, 1992) and competency traps (Levitt and March, 1988; Rosenkopf and Nerkar, 2001). March (1991) identifies that exploitative search can have potential drawbacks for firms that become too reliant on this type of search. A potential problem may occur when a problem can only be solved with knowledge available only externally to the firm's boundaries. Thus, local search can lack the inspiration and variety required for problem solving (Postrel, 2002). Moreover, the frequent use of the same knowledge can lead to myopic behaviour (Levinthal and March, 1993; March, 1991) and cognitive biases (Katila and Ahuja, 2002).

Firms can either reconfigure their knowledge either from inside organisational boundaries (e.g. combinative capability) (Kogut and Zander, 1992), or by integrating knowledge from outside organisational boundaries (e.g. architectural competence) (Henderson and Cockburn, 1994). The exploration of unfamiliar knowledge usually outside their technological or organisational boundaries, will increase their variety of knowledge (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008). The higher the variety, the higher the knowledge for innovation. According to March (1991), externally sourced knowledge enriches the knowledge pool by adding distinctive new variations. Novel variations are essential to firms for the creation of a sufficient amount of choice in solving problems. In other words, exploration should increase new elements to the set of knowledge, improving the possibilities for finding a new useful combination (Fleming and Sorenson, 2001; Nelson and Winter, 1982). Therefore, several scholars considered exploration as a fundamental requirement for the technological change and the ultimate prosperity of the firm (Nagarajan and Mitchell, 1998; Stuart and Podolny, 1996).

Unfortunately, all that glitters is not gold, and the explorative knowledge-search involves considerable risk and uncertainty. This is what March (1991) referred to as the "*vulnerability of exploration*", which argues that due to the higher likelihood of failure involved with the exploration process, its pursuit would yield lower returns than exploitation (although, there should be technological areas in which the opposite is true). As such, there is a trade-off between the advantages derived from increases in knowledge variety, and the level that a firm can effectively manage. Too much variety can lead to issues concerning product reliability, complexity, and consequently involves costs associated with the research process. High levels of exploration may involve increased knowledge integration costs and decreased reliability (Katila and Ahuja, 2002).

Prior empirical studies demonstrate that firms innovating through the exploitation of more familiar technological components generate more useful inventions on average (Fleming, 2001; Kaplan and Vakili, 2015), particularly when familiar components are combined in novel (unprecedented) ways (Arts and Veugelers, 2014). Similarly, Cohen and Caner (2016) demonstrated that exploitation makes a stronger contribution to breakthrough invention as it produces novel ideas that survive more frequently than exploration. As shown by Laursen (2012), the initial trend among scholars was to show the theoretical and empirical impact of local search, whereas more recent contributions focused on understanding why firms tend to predominantly search locally and how can they balance exploratory search to avoid the *"familiarity trap"*. Although, several studies have attempted to answer these questions, research remains to demonstrate how this balance can be achieved.

2.2. Continuous vs. Orthogonal Knowledge-Search

From the contrasting results on the role of exploration and exploitation research focus, it would be sensible to suggest that an appropriate balance between the two research focuses should be the optimal choice for firms' survival and propensity. A few studies considered a firm's novelty level to be a continuous inverted-U shaped curve in relation to firm's performance. However, the operationalisation of the ratio of exploration to exploitation varies amongst past research. Lavie et al. (2010) theorised a conflict-type behaviour by measuring relative levels of each behaviour. Other studies start from the assumption that successful organisations do attempt to simultaneously engage in both exploration and exploitation at the same time, depending on the objectives of separated organisational units (Benner and Tushman, 2003; O'Reilly III and Tushman, 2004) or even through processes (Mom et al., 2009). This latter approach visualises the exploration to exploitation ratio in an orthogonal relationship and it was referred to as firms or managers' capacity to ambidexterity. For example, Cao et al., (2009) shows that firms in resource-rich environments should focus on both exploration and exploitation at the same time, whilst those firms that are resource constrained benefits from advancing one focus more than the other. The optimal ratio between the two research focuses depends heavily on the industrial context and the firm specific set of practices to another (Rosenkopf and Mcgrath, 2011).

Rosenkopf and Mcgrath (2011) provide an extensive overview of the survey-based studies on the exploration-exploitation arena. The study shows that there is both theoretical and operational methodological dissonance. Moreover, differences such as private versus public firms were not taken into account, further decreasing the possibility of direct comparison as well as their generalisability potential. Further discrepancies are displayed in *large-sample archival* studies as they suggest divergent results by taking into account different contexts in which exploration-exploitation is considered. Lavie and Rosenkopf (2006) empirically demonstrated to obtain different results when taking into account exploration from different contexts (e.g. structural domain vs. functional domain exploratory focus), suggesting that different types of explorations could be additive. However, this relationship was later suggested to be a in the form of a balance within each context (Lavie et al., 2011), assumed to be dictated by the costs of managing resources conflicts as well as developing routines.

2.3. Technical and Social Contexts in Knowledge-Search

Studies on exploitation-exploration consider *novelty* as distinct types of *mechanisms* of exposure to new knowledge (i.e. any activities such as learning, innovation, and other strategic behaviour), and their *contextualised position* of the activity (Rosenkopf and Mcgrath, 2011). Mechanisms previously studied included alliance formation (Beckman et al., 2004a; Rothaermel and Deeds, 2004), patents resulting from internal R&D (Benner and Tushman, 2003; Sorensen and Stuart, 2000), acquisitions (Puranam et al., 2006; Vermeulen and Barkema, 2001), mobility (Groysberg and Lee, 2009; Rosenkopf and Almeida, 2003), or new product development (Danneels, 2002; Katila and Chen, 2008). Based on which mechanism these studies focus on, the novelty of these mechanisms can be classified based on the contextualised positions by which the mechanism can be compared with past activity to assess novelty or familiarity.

Two types of contexts for novelty were identified by previous researchers. According to Rosenkopf and Mcgrath (2011), innovation novelty is captured by the technical context whereas inter/intra-organisational relationship is captured by the social context. Part of the technical context has been examined through the patent portfolio of the firm. A patent is the building block on which a firm's product or service is constructed, and the quality of the patent can assess whether it contributes substantially to the extension of existing knowledge (i.e. incremental innovation) or it creates a novel and radical shift from the current field (i.e. radical innovation). This assessment was performed in various ways, for example, prior studies examined whether new patents reside in the same technological classes as prior patents (e.g. Arts and Veugelers, 2014; Fleming, 2001; Kaplan and Vakili, 2015) or whether they cite prior patents in familiar or unfamiliar areas (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001; Sorensen and Stuart, 2000).

The studies focusing on the technical context are based on the evolutionary concept of novelty developed by scholars on the history of technology and innovation studies. Recombination is a process of combination of novel and existing components (Gilfilla, 1935; Schumpeter, 1939; Usher, 1954), resembling the recombinant processes of natural and physical phenomena and other anthropological processes (Arthur, 2007; Basalla, 1989; Hargadon and Sutton, 1997; Henderson and Clark, 1990; Nelson and Winter, 1982; Weitzman, 1998). In innovation the recombination process can be either generated by a new combination of components or a new relationship between previously combined components. For example, Ahuja and Lampert (2001) considered technological novelty when a firm first applies for a patent in a class in which it was not previously familiar. Arts and Veugelers (2014) considered technological novelty as a patent level of new unprecedent combination of subclasses.

This recombination process involves the reorganisation of technological components which can be acquired locally, through the exploitation of familiar components, or externally through the incorporation of distantly sourced components to a particular technological area (March, 1991). As such, part of the studies focusing on the social context of knowledge-search consider novelty to begin at the firms' organisational boundary. Rosenkopf and Nerkar (2001) considered the patent citations to the firm itself as familiar whereas citations to other firms would be considered more novel. Another set of studies focused on the social contexts of the geographic space, in which local search is seen as familiar whilst distant search is unfamiliar. According to Rosenkopf and Almeida (2003) firms' alliances and mobility to distant regions provide higher chances to exposure to diverse knowledge other than the redundant technological know-how. Singh (2005) empirically demonstrated that regional and firm boundaries restrict knowledge diffusion and distance strengthen network collaborations.

Phene et al. (2006) use a more complex approach to novelty which considers different combinations of technological and geographic contexts simultaneously. The study reveals that firms' sourcing local (i.e. national) technologically distant knowledge has a curvilinear effect on breakthroughs whilst sourcing international knowledge which is technologically familiar has a positive impact on breakthrough innovation. To further extend the literature of social contexts, a few studies considered alliances formation decisions as a further context and partners' relationships as the learning activity and assess their development in comparison to pre-existing relationships. This approach assumes that firms entering new partnerships with repeated partners are less novel than first-time partnerships (Beckman et al., 2004b; Kogut and Zander, 1992; Rosenkopf and Mcgrath, 2011).

2.4. Recombinant Novelty within Knowledge-Search

Prior research that mostly drew from the literature of path dependency and technological development (Cohen and Caner, 2016; Dosi, 1982; Levinthal, 1998; Nelson and Winter, 1982) shows that superior performance is enhanced through exploratory search beyond the firm's local domain. Those studies largely associated local search with exploitation (Fleming, 2001) or lower level exploration at best (Rosenkopf and Nerkar, 2001) compared to boundary-spanning search. In contrast to prior studies, Jung and Lee (2016) identified a further dimension of knowledge-search which distinguishes the search target (i.e. what to explore) from the previously analysed boundary dimension (i.e. where to explore). By introducing the search for originality as a distinct dimension, even within local domain a search that target original knowledge can be highly explorative. As such, knowledge that recombines prior knowledge in a novel way can be regarded as original. The study demonstrated that searching original knowledge (i.e. inventions encompassing novel combinations of technological components) and incorporating it into research and development makes local search outperform boundary-spanning search in generating breakthrough inventions. Thus, knowledge-search occurs in a multidimensional space that cannot be captured only by local versus boundary-spanning search (Katila and Ahuja, 2002), whilst other dimensions have to be considered simultaneously (Rosenkopf and Mcgrath, 2011).

Both the existing stock of knowledge and the current search strategies were found to affect the quality of innovation output and innovation performance (Cammarano et al., 2017; Ferreras-Méndez et al., 2015) contributing to the firm economic returns and market value (Hall et al., 2005). Harrigan et al. (2018) further shows that not only radical innovations (Mazzucato and Tancioni, 2008a, 2012) but also firms organisational learning strategy can have an effect on firm performance. For instance, prior-art citations indicating to some degree the embedded novelty of innovation may be a signal of a firm's future value. As such, firms citing novel and exotic technologies are perceived by investors as having higher potential for growth opportunities. Moreover, firms should not rest on the laurels of prior research but continuously increase their novelty over time (Harrigan and DiGuardo, 2017).

Prior studies revealed that a patent's content is rich of information with regard to several aspects of knowledge-search strategies. As such, search strategies not only show a firm decision to build from technologies across broad fields (i.e. what to explore), but also the decision to explore application domains that are new to the firm (i.e. where to explore) (Banerjee and Cole, 2010; Jung and Lee, 2016). Considering multiple dimensions of knowledge-search would provide a deeper insight into the future value of a firm. In particular, the analysis of a firm's search strategy with regard to the boundary dimensions could indicate the risk that might occur whenever a firm rely heavily on searching either inside or outside its organisational boundaries. Therefore, further research is needed to investigate the multiple dimension of knowledge-search impact on firm performance. Recent research suggested, the impact on innovation is different when multiple aspects of knowledge search are considered.

3. Data and Methods

3.1. Sample and Data

The sample comprises a section from the population of the Information and Computer Technology (ICT) companies operating in the US. The ICT sector has been characterised by a period of intense growth over the 1990s. In this period new firms could quickly rise large sums of capital to fund their exploration of commercial opportunities, driven by the rapid growth of the internet (Cockburn and Wagner, 2007). A large number of firms appeared in any of the subsection of the ICT sector, the growth was not only driven by new innovation but also by the excitement of the moment of easy access to capital, unrestricted market entry, and extraordinary valuation of untested new firms. In fact, not every company was profitable, and by the beginning of the twenty-first century this booming period was followed by a drastic collapse of the stock market as well as firm's exit and bankruptcies.

This period of growth and excitement saw an upsurge in the number of ICT technology patents. This was also fuelled by the newly change in the United Stated patent system which led to the patentability of software and business methods. ICT firms could thus file patents regarding their products and business processes, as seen by the significant number of "business methods" patents filed with the USPTO between 1999 and 2002 (Cockburn and Wagner, 2007). The large number of patents raised amongst many the concern with regard to the potential negative consequences of allowing the issue of a large number of low-quality patents. Some people argued that such high level of patents would curb innovation by blocking technological development as well as competitions. This would require new firms entering the market to pay for expensive patents, on the contrary it would allow firms to appropriate and control parts of the market by obtaining curtailing patents with inappropriately broad claims. This makes it hard to clearly understand the value of these patents, as well as their impact on the profitability and growth of ICT firms.

This industrial sector was selected for a number of considerations. First of all, it is a sector with a high number of inventions and with substantial R&D intensity. Second, this sector involves quite an active patenting activity, shown by the number of patents produced each year, as protection from patents can be very important for the firm survival.

According to prior a series of prior studies patents are regarded as meaningful indicator of innovation in this industry (Appleyard, 1996; Podolny et al., 2007; Yayavaram and Ahuja, 2008)

Table 4: Industry Sample

N.	Code	Industry	Firms	% Tot.
1	451020	IT Services	31	4.8
2	451030	Software	181	28
3	452010	Communications Equipment	113	17.5
4	452020	Technology Hardware, Storage and Peripherals	54	8.3
5	452030	Electronic Equipment, Instruments and Components	132	20.4
6	453010	Semiconductors and Semiconductor Equipment	136	21
	Total		**647**	**100**

Financial data for 647 firms operating in the US between 1999 and 2006 is provided by the COMPUSTAT[2] database. Only firms pertaining to the GIC codes from Table 4 are included in the analysis. The sample includes firms with at least 7-year financial data. Patent data is drawn from the newest version of the NBER patent citations database which provides detailed patent related information on around 3.65 million US patents granted between January 1963 and December 2006. The use of patent data will enable the study of a firm's knowledge-search focus impact on innovation and firm's performance. The financial data of all the 647 firms from the COMPUSTAT database was merged with the USPTO patent data. The two databases are merged using the firm CUSIP code and patent application date rather than the patent granted date since the latter varies depending on the speed of the patent review process. The final sample comprises of 647 firms and 4,784 firm-year observations from 1999 to 2006.

3.2. Measures

3.2.1. Dependent Variable:

To analyse the impact of knowledge-search strategies on the perceived market value of a firm this study adopts the Tobin's q, which is a common indicator of market expectations regarding intangible assets from prior research concerning patents value (Hall et al., 2005;

2 https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

Harrigan et al., 2018; Jaffe, 1986). Tobin's q is the yearly ratio between a firm's book market value and its book value of assets (Bronwyn Hall et al., 2005). It is typically used relative to an event in order to acquire investors reaction thereafter (Harrigan et al., 2018).

This study adopts a measure of firm patenting activity which takes into account the quality of innovation for the identification of knowledge-search effect on a firm's innovation performance in accordance with a long body of the literature (Hall et al., 2005; Mazzucato and Tancioni, 2012, 2008; Phene et al., 2006). This measure is constructed in the following method, a firm yearly stock of patent's number of citations, is divided by the total industry yearly sum of patents. This approach takes into account both time and industry truncation without reducing the sample size.

This study aims to investigate whether the explorative knowledge-search is linked to higher likelihood of unsuccessful inventions. In line with previous research, patents receiving no future citations are considered as failures (Arts and Veugelers, 2014; Singh and Fleming, 2010). This measure is constructed as a dummy variable, in which unity identifies a firm with an average stock of weighted patents citations equal to one, whilst zero correspond to one or more forward citations. Firms that have not produced any patents in a given year are considered as failures.

3.2.2. Independent Variables:

This study employs the concept of a two-dimensional representation of the firm's search focus (Katila and Ahuja, 2002) of which can vary not just in their *scope* (local versus distant) but in their *depth* defining the degree of reused or exploited knowledge. In this sense, firms can use and reconfigure their existing knowledge repeatedly leading to varying degrees of familiarity. This study builds on this idea and further tries to identify the differences in innovation performance of firms focusing on different levels of the two search focuses and their eventual impact on a firm's economic performance. Following Katila and Ahuja (2002), this study uses firms' patenting activity to distinguish their type of search focuses. The more the use of knowledge the more deeply the knowledge is known. The average number of times a firm repeatedly used the citations in the patents it applied for. The *search depth* variable (DEPTH) is created by measuring the number of times on average each backward citation in year *t* was repeatedly used in the past five years. The sum of the occurrences was then divided by the total number of previous citations that the company received in the previous five years. More formally, the search depth of a firm *i* in year *t-1* is calculated as following:

$$DEPTH_{it-1} = \frac{\sum_{y=t-6}^{t-2} Repetition\ Count_{iy}}{Total\ Citations_{it-1}} \qquad \text{(eq.1)}$$

The variable *search scope* (SCOPE) defines knowledge that is explored outside the expert area of the firm. The proportion of previously unused citations in a firm's focal year list of citations. This correspond to the share of citations in a focal year that were never used in the previous five years by that firm. For example, a firm with ten patents in a given year, each one of them cited 10 other patents. Eight out of ten citations are new to the firm (i.e. they have never been previously cited by the focal firm) resulting in the firm's knowledge search scope of 0.8. Regarding the previously used citations in each patent, one has been used twice whereas the other three times resulting in knowledge-search depth of the firm is 0.5. Thus, the search scope of a firm *i* in year *t-1* is calculated as following:

$$SCOPE_{it-1} = \frac{New\ Citations_{it-1}}{Total\ Citations_{it-1}} \qquad \text{(eq.2)}$$

This study considers a further knowledge-search dimension which identify the recombinant novelty of the target knowledge adopting the measure of novel recombination developed from previous research (Arts and Veugelers, 2014). This measure is constructed by averaging the number of novel subclass pairs by the patent total number of subclass pairs. To construct the firm's level of novel recombination encompassed into knowledge-search, the yearly sum of each patent recombinant novelty was adopted. Consequently, the novelty of a firm *i* in year *t-1* is calculated as following:

$$NOVELTY_{it-1} = \sum \frac{First\ time\ Technological\ Class\ Combination_{it-1}}{Total\ Number\ of\ Technological\ Classes_{\ it-1}} \qquad \text{(eq.3)}$$

Processes of knowledge-search do not always lead to the creation of technological novelty. The existing literature shows that the introduction of distantly sourced technologies does not always provide more successful inventions or higher chances of breakthrough innovation (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Although the pursue of exploratory activities increases the variety of technological components at disposal for the firm (March, 1991) increasing the recombinatory potential, this does not necessarily translate into novel technologies entering the market. For example, a firm can just borrow unfamiliar knowledge to them, to replicate existing technologies at either a higher quality or cheaper price, without generating novel inventions. Similarly, reusing more familiar technology might reduce experimentation and variability, reducing the chances to generate something exceptionally valuable (Ahuja and Lampert, 2001; Levinthal and March, 1993). However, recent research demonstrate that familiar technologies that are recombined into unprecedented 'novel' recombinations provide the most valuable inventions (Arts and Veugelers, 2014). Thus, both exploitaiton as well as exploration should increase a firm performace as long as the use of technological components are recombined in novel unprecedented ways. Therefore, an interaction term between search depth and recombinant novelty is used to indicate whether knowledge-search processes that give birth to novel inventions increases the value of the firm.

3.2.3. Control Variables:

The regression model includes some firm characteristics control variables that might directly affect inventive success. The level of expenditures on research and development might affect the probability to innovate, thus variable *R&D expenditure* (RES) capture firm research inputs was included in the model. The variable *corporation size* (SIZE) measured as the number of employees is used as a proxy for firm size. Size is an important parameter as it is related to the innovation activity since larger firms are usually more diversified and can benefit from economies of scale. For example, Lewin and Massini (2003) revealed a positive relationship between R&D activities and firm's size. Usually, larger firms have stronger cash flow as well as higher assets to fund innovation, whereas small firms rely more on innovative dynamics, whereas large firms are expected to rely more on market power strategies (Pianta and Vaona, 2007). Furthermore, the lag of a firm Tobin's q ratio and the lag of the stock of assets were used as further control variables. All independent and control variables are lagged by one year.

Table 5: Variables Description

N.	Symbol	Description	Transformation	Source
1	TOBIN Q_{it}	Market value over the book value of assets of firm *i* in year *t*	$\log(1+x_{it-1})$	COMPUSTAT
2	$ASSETS_{it-1}$	Total Assets of firm *i* in year *t-1*	$\log(1+x_{it-1})$	COMPUSTAT
3	RES_{it-1}	Research and Development spending of firm *i* in year *t-1*	$\log(1+x_{it-1})$	COMPUSTAT
4	$SIZE_{it-1}$	Number of Employees of firm *i* in year *t-1*	Yearly Sum $\log(\Sigma x_{it})$	COMPUSTAT
5	$FAILURE_{it}$	Dummy for failure of firm *i* in year *t*	Dummy	NBER
6	$PATW_{it}$	Stock of weighted citation patents of firm *i* in year *t*	Yearly Sum $\log(\Sigma 1+x_{it})$	NBER
7	$DEPTH_{it-1}$	Yearly mean Search Depth of firm *i* in year *t-1*	Yearly Mean $\log(1+(\Sigma x_{it})/n)$	NBER
8	$SCOPE_{it-1}$	Yearly mean Search Scope of firm *i* in year *t-1*	Yearly Mean $\log(1+((\Sigma x_{it})/n)$	NBER
9	$NOVELTY_{it-1}$	Technology Recombination of firm *i* in year *t*	Yearly Mean $\log(1+((\Sigma x_{it})/n)$	NBER

3.3. Statistical Method and Analysis

This study employs cross sectional time series regressions with random-effects models and generalised least squares (GLS) estimators. Prior research (Beckman et al., 2004a; Lavie and Rosenkopf, 2006) shows that using fixed-effects can substantially decrease the degrees of freedom and produce unstable results for panels over short time periods. Fixed-effects models predict annual changes in the dependent variables which is not the purpose of this research, instead the interest lies in observing overall knowledge-search dynamics. Furthermore, since this study involves volatile flow data, and not slowly changing stocks, the individual effects are not likely to be correlated with the independent variables and thus capture the sample correlation between the dependent and the independent variable. Furthermore, an individual fixed effects approach would fail to capture the dynamism of firms strategies, as firms change strategies over time in response to market signals (Mazzucato and Tancioni, 2012). To control for firm heterogeneity this study adopts the generalised estimating equations (GEE) regression approach (Katila and Ahuja, 2002). This accounts for autocorrelation due to the repeated yearly measures of the same firms from the panel data by estimating the correlation structure of the error term (Liang and Zeger, 1986). To control for firm heterogeneity every model includes a 1-year lagged dependent variable. Lastly, to account for any overdispersion in the data the results are reported with robust standard errors.

3.4. Summary Statistics

The final sample is comprised of an unbalanced panel data with a total of 647 unique companies with at least 6-year financial observations between 1999 and 2006. As shown in Table 5, several variables including returns on assets, Tobin's q, size, and research and development spending were transformed due to error terms and skewness problems. Table 6 shows the variables with their means and variances. Tobin's q, research and development (RES), and weighted citation patent (PATW) were transformed into logarithmic values.

Table 6: Descriptive Statistics

Statistic	TOBIN_Q	ASSETS	SIZE	RES	PATW	FAILURE	DEPTH	SCOPE	NOVELTY
Mean	1.326	4.645	0.741	2.830	0.588	0.115	0.346	0.194	0.458
St. Dev.	0.634	1.695	0.870	1.632	1.232	0.320	0.630	0.256	0.905
Min	0.038	0.595	0.003	0.000	0.000	0	0.000	0.000	0.000
Max	4.692	11.164	5.800	8.959	8.252	1	3.985	0.693	6.642
N	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784

Table 7 shows the Pearson's bivariate analysis showing the correlation coefficients that measure the strength of the relationship between the variables. Overall, there are not highly correlated variables throughout the sample. Interestingly, search depth and weighted patent citations (PATW) are significantly correlated. In line with prior research, firm size is strongly (75%) and significantly correlated with R&D spending.

Table 7: Correlation Coefficients Table

	TOBIN_Q	ASSETS	SIZE	RES	PATW	FAILURE	DEPTH	SCOPE	NOVELTY
TOBIN_Q		0.04*	0.08*	0.17*	0.19*	0.02	0.14*	0.09*	0.15*
ASSETS			0.81*	0.85*	0.45*	0.11*	0.39*	0.28*	0.57*
SIZE				0.72*	0.46*	0.06*	0.32*	0.20*	0.60*
RES					0.48*	0.12*	0.42*	0.31*	0.61*
PATW						-0.17*	0.53*	0.32*	0.81*
FAILURE							0.14*	0.18*	0.04
DEPTH								0.14*	0.62*
SCOPE									0.36*

Note: * p<0.01

4. Results

4.1. Firm Innovation Quality

Table 8 reports the results of the first regression analysis with patent quality measure (PATW) and innovation Failure (FAILURE) as the dependent variable. The regression result shows some interesting insight regarding the impact of firm's knowledge-search strategy on innovation outcome. First of all, both search scope and search depth estimators are positive and significant, although search scope has a stronger positive relationship than search depth. Search scope is found to substantially increase the quality of innovation but at the same time increase the likelihood of failures. This is in line with the tension view, exploring new knowledge increases the variety of knowledge and consequently the recombinatory potential of innovation (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Lazonick, 2005; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008). However, the results also confirm that the exploration process can be uncertain and risky for the firm that pursue it, as this is associated with higher exposure to innovation failure (D'Este et al., 2018).

The regression analysis revealed two further similarities to the literature. Firms should balance the exploration of new possibilities with the exploitation of their existing competences through processes of 'ambidexterity' (March, 1991; O'Reilly III and Tushman, 2004). As exposed by the strong and positive estimator of the interaction term (DEPTHxSCOPE), knowledge-search is particularly beneficial when a firm focuses simultaneously on both exploration and exploitation, and this seems to drastically reduce the likelihood of failures. Furthermore, in line with D'Este et al., (2018) both search depth and search scope have an inverted-U relationship with patenting failures, suggesting that the intensity of engagement in knowledge search activities attenuate the initial positive relation between knowledge-search and failures. Interestingly, both knowledge-search processes have also an inverted-U relationship with weighted patent citations which highlight the detrimental effect of firms intensive focus on either one of the search processes.

The novel approach introduced in this research is to include the target technology a firm aims at during the process of searching. The regression analysis shows that firms generating novel recombinant technologies can substantially increase their innovation quality, although this is only relevant when novelty is combined with exploratory search. Interestingly, novelty created through the exploitation search does not increase the quality of its innovation outcome, as the interaction term between novelty and search depth is just as positive as search depth on its own. Furthermore, generating novel recombination from both search processes decreases the likelihood of inventions failures.

Table 8: Effect of Knowledge-search on Firm's Stock of Weighted Patent Citations and Innovation Failures

	PATW								FAILURE							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Constant	-0.499***	-0.249***	-0.160**	0.009	-0.211***	-0.226***	-0.025	-0.137**	-1.890***	-1.845***	-1.880***	-2.036***	-1.831***	-1.820***	-1.849***	-1.995***
	(0.088)	(0.081)	(0.078)	(0.062)	(0.080)	(0.080)	(0.067)	(0.069)	(0.155)	(0.160)	(0.161)	(0.166)	(0.160)	(0.161)	(0.156)	(0.160)
DEPTH		0.706***	0.282***	0.005	0.524***	1.079***	0.556***			0.281***	0.376***	0.491***	0.238***	0.657***	0.234***	
		(0.024)	(0.033)	(0.027)	(0.029)	(0.061)	(0.020)			(0.039)	(0.051)	(0.054)	(0.047)	(0.103)	(0.038)	
SCOPE		0.863***	0.462***	0.153***	3.984***	0.773***		1.034***		1.015***	1.105***	1.246***	1.862***	0.955***		0.861***
		(0.057)	(0.059)	(0.047)	(0.296)	(0.058)		(0.049)		(0.099)	(0.103)	(0.105)	(0.483)	(0.102)		(0.095)
DEPTHxSCOPE			2.918***	0.434***							-0.696***	0.147				
			(0.159)	(0.134)							(0.253)	(0.271)				
NOVELTY				1.069***								-0.454***				
				(0.020)								(0.048)				
SCOPE_SQ					-4.906***								-1.315*			
					(0.457)								(0.735)			
DEPTH_SQ						-0.164***								-0.161***		
						(0.025)								(0.042)		
SCOPExNOVELTY							2.166***								-0.321***	
							(0.043)								(0.091)	
DEPTHxNOVELTY								0.502***								-0.071***
								(0.010)								(0.022)
ASSETS	-0.075***	-0.095***	-0.081***	0.027*	-0.091***	-0.094***	0.002	-0.029*	0.069**	0.053	0.050	0.009	0.054	0.053	0.050	0.054
	(0.020)	(0.018)	(0.018)	(0.014)	(0.018)	(0.018)	(0.015)	(0.016)	(0.035)	(0.036)	(0.037)	(0.038)	(0.036)	(0.037)	(0.036)	(0.036)
RES	0.251***	0.110***	0.068***	-0.046***	0.088***	0.098***	-0.030**	0.040**	0.170***	0.085**	0.099***	0.160***	0.077**	0.072**	0.168***	0.156***
	(0.019)	(0.018)	(0.017)	(0.014)	(0.018)	(0.018)	(0.015)	(0.015)	(0.033)	(0.035)	(0.036)	(0.037)	(0.036)	(0.036)	(0.035)	(0.035)
SIZE	0.413***	0.430***	0.374***	-0.042*	0.413***	0.424***	0.084***	0.161***	-0.227***	-0.202***	-0.189***	-0.040	-0.207***	-0.211***	-0.180***	-0.174***
	(0.031)	(0.028)	(0.028)	(0.023)	(0.028)	(0.028)	(0.024)	(0.025)	(0.050)	(0.051)	(0.052)	(0.054)	(0.052)	(0.052)	(0.052)	(0.052)
Observations	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784
Log Likelihood	-6,914.476	-6,441.973	-6,278.342	-5,161.921	-6,384.849	-6,419.863	-5,545.322	-5,733.374	-1,651.359	-1,582.537	-1,578.781	-1,530.935	-1,580.904	-1,574.407	-1,628.723	-1,601.458
Akaike Inf. Crit.	13,846.950	12,905.940	12,580.680	10,349.840	12,793.700	12,863.730	11,112.640	11,488.750	3,320.718	3,187.074	3,181.563	3,087.871	3,185.807	3,172.814	3,279.447	3,224.916

Note: Cross-section dimension (firms): 647

The table gives parameter estimates including robust standard errors in parentheses.

* p<0.1; ** p<0.05; *** p<0.01

4.2. Firm Perceived Value

The second objective set out for this research is to analyse the perceived market value of the firm's stock of technological novelty and whether this improves the value of knowledge-search strategy in which a firm engages.

The regression analysis in Table 9 shows the relation between firm's innovation activities, such as processes of knowledge-search and the stock of technological novelty and the firm's perceived value expressed in Tobin's Q. The coefficient of search depth and scope are positive and significant, indicating that both processes are perceived as valuable. Both coefficient for the squared terms of search depth and scope are positive and significant indicating a linear relationship between these and firm's market value. Firms involved simultaneously in both search processes are perceived as the most valuable indicated by the interaction term. Interestingly, the introduction of the stock of technological novelty reduces the significance of this interaction. The estimator for the stock of technological novelty is positive and significant, which provides evidence of the value of novelty increases investors' expectations on the future profitability of the firm.

The estimator of the interaction terms between scope as well as depth and novelty are both positive and significant. Technological novelty is combined with search scope gives a higher positive effect on firm's market value, which indicates that outsourced technologies used to generate novel inventions are perceived as the highest contributor to firm's future prosperity. Interestingly, firm that generate inventions which encompass novel recombinations through exploiting familiar knowledge experience a decreased positive impact on their market value. In contrast to the previous results on weighted patent citations, the squared search scope and search depth estimators are positive and significant suggesting that both exploration and exploitation have a linear relationship with firm's perceived market value. This is particularly evident for search scope.

4.3. Robustness of the Results

The sensitivity of the results was carried out in several ways. The regression analysis was performed using a 2-year lag of the independent variables of interest. In line with prior research the knowledge search loose magnitude, which highlight the diminishing impact of acquired knowledge (Ahuja and Katila, 2001; Harrigan et al., 2018).The regression analysis was carried out using a restricted sample, only including firms with a minimum of seven consecutive year of observations and the results of the regression analysis on Tobin's q were unchanged. Further robustness of the results was assessed by controlling for firm heterogeneity adopting the generalised estimating equations (GEE) regression approach (Katila and Ahuja, 2002); a one year lagged dependent variable was adopted to control for firm heterogeneity in every model; robust standard errors were used to account for any overdispersion in the data.

As a further robustness test we performed a further regression (Model 10) using a dummy variable as a proxy for the change in the US patenting system which occurred in 1999 and was effective by 2001. From 2001 onwards, information on firm's innovation was publically available at the moment of patent application thus, investors could quickly assess their future prosperity based on firms' most recent technological advances. The American Inventor's Protection Act of 1999 requires publications of all applications after 18 months but excepts applicants opting to make a declaration that a patent will not be sought in a foreign jurisdiction requiring 18 months publication (35USC §122). Thus, until 2001 US patents were only published once the patent has been granted, maintaining secrecy for those inventors whose applications have not been successful (Harhoff et al., 2003). Therefore, investors had only limited knowledge of a firm failures and successes prior to the patent's act. Whereas after 2001 investors could draw knowledge of the most recent firm's innovation activity allowing them to assess whether firms would be profitable in the near future.

Table 9: Effect of Knowledge-search on Firm's Tobin's

	TOBIN_Q												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Constant	0.699***	0.745***	0.710***	0.758***	0.765***	0.773***	0.771***	0.751***	0.755***	0.743***	0.840***	0.773***	0.817***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.046)	(0.044)	(0.054)
DEPTH		0.072***		0.073***	0.049***	0.042**	0.064***		0.078***		0.045**	0.042**	0.033*
		(0.012)		(0.012)	(0.017)	(0.018)	(0.012)		(0.012)		(0.018)	(0.018)	(0.017)
SCOPE			0.093***	0.096***	0.073**	0.064**		0.103***		0.111***	0.050	0.064**	0.031
			(0.029)	(0.029)	(0.031)	(0.031)		(0.029)		(0.029)	(0.031)	(0.031)	(0.034)
DEPTHxSCOPE					0.160*	0.093					0.096	0.093	0.037
					(0.083)	(0.089)					(0.089)	(0.089)	(0.095)
NOVELTY						0.027**					0.022*	0.027**	0.029**
						(0.013)					(0.013)	(0.013)	(0.012)
SCOPExNOVELTY							0.103***						
							(0.026)						
DEPTHxNOVELTY								0.029***					
								(0.006)					
SCOPE_SQ									0.135***				
									(0.044)				
DEPTH_SQ										0.027***			
										(0.005)			
TOBIN_Q1	0.596***	0.587***	0.592***	0.584***	0.583***	0.582***	0.583***	0.585***	0.584***	0.585***	0.573***	0.582***	0.570***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.017)
ASSETS	-0.047***	-0.055***	-0.051***	-0.059***	-0.060***	-0.059***	-0.056***	-0.054***	-0.058***	-0.057***	-0.055***	-0.059***	-0.086***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
SIZE	0.087***	0.083***	0.088***	0.085***	0.081***	0.070***	0.066***	0.069***	0.085***	0.087***	0.067***	0.070***	
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	
After2001											-0.084***		
											(0.017)		
RES													0.076***
													(0.010)
Observations	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784	4,784
Log Likelihood	-3,235.403	-3,218.139	-3,230.168	-3,212.516	-3,210.639	-3,208.469	-3,210.265	-3,216.310	-3,213.512	-3,216.085	-3,196.388		
Akaike Inf. Crit.	6,488.807	6,456.278	6,480.335	6,447.031	6,445.278	6,442.937	6,442.530	6,454.620	6,449.023	6,454.169	6,420.775		

Note: Cross-section dimension (firms): 647

The table gives parameter estimates including robust standard errors in parentheses.

* p<0.1; ** p<0.05; *** p<0.01

5. Discussion

The empirical analysis demonstrated that firm's engagement in exploratory research is associated with higher exposure to innovation failure. In line with the literature, firms exploring unfamiliar knowledge experience a much higher risk of generating failures, than exploiting familiar technologies. Indeed, too much variety can lead to issues concerning product reliability, complexity, and consequently involves costs associated with the research process (Argyris and Schön, 1997; Carlile, 2002; Dosi, 1988; March, 1991). However, in contrast to prior research, the analysis shows that high levels of exploration, for instance, decreases the likelihood of a firm's failure. However, prior research demonstrated that firms can learn how to reduce failures through several mechanisms, for example inferential-based learning and experimental-based learning (D'Este et al., 2018). The empirical results suggest a further mechanism to reduce the negative effect of the exploratory search. This occurs when exploratory search is employed to generate technological novelty, which drastically decreases invention's failures whilst increasing invention's quality.

In line with prior findings (Harrigan et al., 2018), the exploration of unfamiliar knowledge is perceived as a potential indication of a firm's future value creation. The exploration process is assumed to be linked to increases in variety of knowledge, with the potential to further increase the likelihood of recombinant novelty, and in turn increase the likelihood of generating breakthrough innovation (Ahuja and Lampert, 2001; Arts and Veugelers, 2014; Kaplan and Vakili, 2015). This study proposed that exploration can lead to two outcomes, either the generation of an existing invention (i.e. unfamiliar for the firm but not necessarily novel to the market) or to a novel invention entering the market. The empirical analysis demonstrated that investors ultimately value more the creation of technological novelty from the pursuit of exploratory activity than any other strategic knowledge search process. Accordingly, the results show that firms that generate novel inventions through the exploration of unfamiliar knowledge, increase their effect on market value, whereas generating novel recombinations through the exploitation of familiar knowledge, decreases firm's market value.

Firms that focus simultaneously on both knowledge-search processes experience the highest impact on market value supporting the 'ambidexterity' concept of balance between the exploration of new possibilities with the exploitation of their existing competences (March, 1991; O'Reilly III and Tushman, 2004). However, investors seem to value firms involved in intense exploration processes, as those firms involved in high levels of exploration experience a similarly high impact on market value. Thus, any extent of exploratory search for knowledge outside the firm competences does not increase the uncertainty around a firm market value despite the challenges that this may involve.

This study is subject to a number of limitations. Firstly, the analysis does not control for other knowledge-search processes. Here, the analysis only accounts for the technical context, whereas inter/intra-organisational relationships captured by the social context are not considered (Rosenkopf and Mcgrath, 2011). As such, external knowledge can be accessed through assimilating information from existing knowledge bases (e.g. patents, scientific publications) and/or by working closely with external partners. This study does not capture the knowledge assimilated through scientific publications, neither through merger and acquisitions. Furthermore, the construction of the analysis might introduce the potential of reverse causality influencing the results. For instance, funding may have increased costly processes of exploration or ambidexterity in the first place, which further down the line, further increases funding of the research process.

6. Conclusion

Firm patenting information informs investors about firm's future value (Bessen, 2009; Hall et al., 2000). This study sheds light on how investors perceive firms' innovation as a potential asset for firm growth. Practitioners must consider investors' expectations because they need access to funding for their strategic decisions (Harrigan et al., 2018). Existing research suggests that firms owning patents that cite distantly sourced technologies have higher market value and thus considered to have higher opportunities for growth (Harrigan et al., 2018). However, prior studies failed to consider the orthogonal dimension of the two searh processes, thus provide no evidence of the impact of the exploitation search nor on the symultaneous exploration-exploitation process. This study contributes to the existing literature by showing that investors respond positively to both exploration as well as exploitation knowledge-search process carried out by the firm. Exploration of unfamiliar knowledge is regarded as a better opportunity for growth attracting much more market value than exploiting existing knowledge. Engaging in both search approaches simultaneously is seen as the most promising activity for future value.

In contrast to the existing literature that portrays exploration as a direct link to novel inventions (Ahuja and Lampert, 2001; Levinthal and March, 1981; March, 1991; Rosenkopf and Nerkar, 2001), this study contributes to the organisational learning literature in two ways. Firstly, this study shows a further mechanisms of risk adversity from firm’s exploratory search. As the exploratory search is risky and uncertain due to increased innovation failures (D’Este et al., 2018), firm should should adopt mechanisms to reduce risks. This study proposes that firms shpould engage in the creation of technological novelty whenever they engage in exploratory search. Secondly, this study exposes that exploration does not necessarily lead to novel products. In this study technological novelty is considered as a first-time occurrence of a combination between technological components (i.e. Arts and Veugelers, 2014; Verhoeven et al., 2016) that can generates from either one knowledge-search process. The empirical results demonstrated that exploring is generally perceived as valuable but through the creation of technological novelty exploratory search can signal a winning strategy for the firm’s future prosperity. Furthermore, this approach may be used by investors for betting on the potential future technological and economic prosperity of firms. To indicate a firm inventive prowess, this approach adopts *ex-ante* measures of a firm’s organisational learning process. These may be more useful for investors than *ex-post* measures of patents quality, as these are not immediately available at the time of innovation (Harrigan et al., 2018).

Chapter III

RECOMBINANT NOVELTY, KNOWLEDGE-SEARCH AND FIRM SURVIVAL

1. Introduction

There is a growing body of literature focusing on the impact of innovation on firm survival. The first studies looked at the difference between innovative firms and non-innovating firms, whilst others looked at the differences between innovating and non-innovating industries (Audretsch, 1995; Audretsch and Mahmood, 1995). More recent studies examined in more detail the firm's innovative activity, such a patenting and trade-marking, which was found to increase the likelihood of firm survival (Cockburn and Wagner, 2007; Helmers and Rogers, 2010), Despite the general positive impact, firms owning highly cited patents are not immune to bankruptcy nor exit through merge and acquisition (Cockburn and Wagner, 2007), which rises some concerns regarding the risks involved in the management of radical innovation. This paper borrows empirical indicators form the body of the literature that focuses on breakthrough innovation (Arts and Veugelers, 2014), and knowledge-search processes (Katila and Ahuja, 2002), to examine the risk of failure involved in the management of the innovation process.

Patents are thought to substantially improve a firm's survival advantage as they help in improving their competitive positions through several mechanisms such as excluding competitors, supporting higher margins, rising rivals' costs, and signalling quality to the market. Interestingly, firms owning more patents are less likely to be acquired, whereas owning highly cited patents make them more likely to merge or be acquired (Cockburn and Wagner, 2007). As the novelty increases the usefulness as well as the likelihood of breakthrough innovation, whilst increasing the risks of failure (Arts and Veugelers, 2014), this paper proposes to examine the link between the firm generation of novelty and firm risk of exit via merger or acquisition as well as failure. In the first instance, certain firms may decide a priori to sell their novel ideas to other firms, whereas in the second instance novelty may not be useful and only increase the mortality rate of the firm. As such, firm's exit does not correspond necessarily to the business closure. The business activity can indeed be competitive and just taken over by another firm. Extending prior research, this study contributes to the survival literature by controlling for firm exit due to delisting from exit via merger or acquisition. This construction allows the distinction between firms that strategically intend to merge or being acquired from those that want to endure.

This paper further account for the level of knowledge-search that firm pursue. Prior findings exposed that firm involved in the strategic process of exploiting technologies from familiar areas (Colombelli et al., 2013) increase their survival rate. However, several researchers pointed out that firm exploration of unfamiliar knowledge is a critical asset for the innovating firm (e.g. Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001). Although high levels of exploitation are expected from firms operating in particularly in the ICT sector (Breschi and Malerba, 1997; Marsili, 2001), this study argues that potential acquirers may value firms owning a broad knowledge, as this is seen as potential for future growth. Thus, the exploration knowledge-search increases firms' likelihood of exit via merger/acquisition whilst reducing their chances of failure.

This study contributes to the literature on survival analysis by adopting the distinction of different types of exit procedures. Secondly, this study contributes to the literature on technological novelty by showing a distinct perspective on the risks associated with the process of generating novelty. Lastly, this study contributes to the organisational learning literature by further increasing the evidence that a balance between distinct search processes is desirable the health of an organisation. The remainder of this paper proceeds as follows. Section 2 presents the findings from prior study in the firm survival literature are briefly summarised and the link with innovation is described. Section 3 contains a short description of the dataset used for the analysis which combines financial data and patent data for 911 firms from the ICT sector and 4,661 firm-year observations between 1980 and 2001. Furthermore, the Cox proportional hazard model regression and the covariates are described in detail, and the result from the Kaplan-Meier survival curve comparing firms employing two distinct types of knowledge-search. Section 4 reports the results from the multivariate survival models for the analysis of the effect of knowledge-search and technological novelty on firm's mortality rate. Finally, Section 5 offers some implications for the findings and Section 6 expands on the contribution to the literature.

2. Background Literature

2.1. Patents and Firm Survival

Most prior research focusing on explaining firm survival has focused on firm-level characteristics such as age, size and financial condition (Hopenhayn, 1992; Jovanovic, 1982). Other research stressed the role of the market, the economic environment and the geographical position of the firms (Cooley and Quadrini, 2001). Some empirical findings exposed that firm survival is positively associated with firm size and firm age (Caves, 1998; Geroski, 1995; Sutton, 1997) as small and younger firms exhibit higher failure rates. Age is thus a proxy for the accumulation of information about technology, markets and a firm's own cost function (Audretsch, 1995). A greater stock of accumulated knowledge leads to higher survival rates (Cockburn and Wagner, 2007). Furthermore, the point in the technology or industry life cycle in which a firm operates is a significant indicator of firm's survival (Agarwal and Gort, 1996; Suarez and Utterback, 1995). Lastly, failure is positively associated with overall industry entry rates and average price cost margins (Audretsch, 1991; Audretsch and Mahmood, 1995). Agarwal and Audretsch (2001) demonstrated that the effect of size as well as age change across different sectors depending on the industry life cycle and the technological regime. Size should be more likely to matter during the formative stage of an industry when innovation activities are moderately routinised and small firms can achieve successful strategic positions by filling some markets niches that are left empty by incumbents (Caves and Porter, 1977).

Fama and French (2004) reported a substantial increase in the number of new lists at the NASDAQ between 1973 and 2001, followed by a sharp decline in survival rates over time. Furthermore, they find that firms that survive show higher profitability and growth rates. Moreover, Seguin and Smoller (1997) find that lower priced stocks have a higher mortality rate than high priced issues. Interestingly, market capitalisation does not influence firms' mortality rates. Chava and Jarrow (2004) find little predictive power by accounting variables when market-based measures are already included in the model. In contrast, Beaver et al. (2005) found additional explanatory power of financial information.

Kauffman and Wang (2003) focused on the survival of the internet transaction business model and found that firms which distribute physical goods through the internet and firms which target both consumers and business markets, have longer survival times. Van der Goot et al. (2009), found that surviving firms are associated with lower risk indications in the IPO prospectus, higher underwriter reputation, higher investor demand for the shares issued at the IPO, lower valuation uncertainty, higher insider ownership retention, a lower NASDAQ market level, and a higher offer to book ratio compared to non-survivors.

Ericson and Pakes (1995) focus on the effect of R&D spending by firms on the likelihood of survival. Through exploring the technological landscape firms improve their efficiency and profitability and consequently their survival rates. Firms then strategically learn distinct competences to increase their likelihood of survival. Nelson and Winter (1982) stress that investment in R&D and innovation lead to improvements of firms' productivity levels. Some researchers adopted R&D investment as a proxy for innovation activities and found that they are positively associated with survival rates. Other researchers used output measures of innovation such as the impact of architectural innovation (Christensen et al., 1998) and the number of product innovations (Banbury and Mitchell, 1995). The introduction of product innovation characterises the early stage of the cycle while process innovation becomes more important when the sector comes to maturity (Cefis and Marsili, 2006, 2005). Helmers and Rogers (2010) adopt patents applications and trademarks as a proxy for a firm's intellectual property to show that both negatively influence the failure rate.

Most of the literature on patents' value has focused on indirect measures of their impact on profitability, such as stock market value of the firm. Relatively little systematic evidence has been gathered on relationship between patenting and more basic indicators of firm performance such as growth and survival (Cockburn and Wagner, 2007). The analysis of firms' intangible assets may be particularly difficult to identify among the noisy uncertainty of stock market valuation, and this evaluation could prove to be useful for small firms or new entrants to a market. Mann and Sager (2007) found some correlation between patenting and different proxies for success in amongst software start-ups. Furthermore, the private returns of holding software patents varies greatly between firms in the same industry segment. Cockburn and Wagner (2007) focused on the relevance of patents for the success of the dot-com firms and found that patenting is positively correlated with firm survival. Interestingly, firms owning highly cited patents make them more likely to be acquired (Cockburn and Wagner, 2007). Jensen et al. (2008)

found that trademarking is associated with greater survival for new firms but found that patenting has no association with survival. Vismara and Signori (2014) further analysed the impact of patents and R&D on firm survival by taking into account the heterogeneity of delisting. They found that firms with larger patent portfolio are more likely to exit via merger/acquisitions, whereas they are less likely of delist due to firm failure. Higher R&D investment increases the likelihood of exit via delisting.

2.2. Firm Search Process and Firm Survival

Prior studies on firm's survival analysis treated innovation much like a black box, mostly using dummies variables for the patenting activity or indicators of patent count or citations at best. Patent content is however rich of information regarding the processes of search that a firm can adopt to generate novelty and increase their innovation output (Katila and Ahuja, 2002). Empirical research shows that firms tend to search locally (Martin and Mitchell, 1998; Patel and Pavitt, 1997; Stuart and Podolny, 1996; Tripsas and Gavetti, 2000) and that firms display remarkably little sign of technological variety (Patel and Pavitt, 1997). However, local search often lacks inspiration and variety required for problem solving activities, for knowledge recombination (Fleming and Sorenson, 2001; Rosenkopf and Nerkar, 2001; Rothaermel and Alexandre, 2009). Moreover, intense focus on local search can lead to myopic behaviour and cognitive biases (Levinthal and March, 1993; March, 1991). Accordingly, the disadvantages of local search can be damaging and eventually lethal to organisation that relies too much on this type of search.

To increase the variety of knowledge, firms become involved into exploratory processes of unfamiliar knowledge usually outside their technological or organisational boundaries (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008). According to March (1991), externally sourced knowledge enriches the knowledge pool by adding distinctive new variations which are essential to firms for the creation of a sufficient amount of choice in solving problems. In other words, exploration should increase new elements to the set of knowledge, improving the possibilities for finding a new useful combination (Fleming and Sorenson, 2001; Nelson and Winter, 1982). The exploration process also involves considerable risk and uncertainty and the possibility that its pursuit would yield lower returns than exploitation. High levels of exploration may involve increased knowledge integration costs and decreased reliability (Katila and Ahuja, 2002). As such, there is a trade-off between the advantages derived from increases in knowledge variety, and the level that a firm can effectively manage. Too much variety can lead to issues concerning product reliability, complexity, and consequently involves costs associated with the research process.

Yet almost no research has analysed the potential negative consequences of the mismanagement of their knowledge-search processes. Colombelli et al. (2013) explores the link between knowledge-search processes and firm survival rates. They found that technological variety enhance firm survival while citing technological distant inventions is associated with firm mortality. In this perspective, the generation of knowledge and the introduction of innovation are the results of cumulative patterns, learning dynamics and path dependence. This finding seems to resonance the negative effect of inventions drawing from technologically distant prior citations on technological impact, in some industries (Nemet and Johnson, 2012)[3], whereas a positive effect was found in others (Keijl et al., 2016).

Prior research mostly neglects potential external effects that could largely affect the firm's ability to survive, and do not distinguish between distinct types of delisting, such as exit via bankruptcy from exit via merger or acquisition. The reasons for mergers and acquisitions are complex and thus, cannot be easily thought of as failures. Generally, a business in financial difficulty might seek to merge or to be acquired to gain access to financial capital. However, a healthy business might also be acquired due to its growth potential or as a way for stakeholders to maximise their profits (Kauffman and Wang, 2003). Thus, recognising the complex nature of the drivers of distinct survival outcomes is essential for a better identification of the mortality risks. Similarly, avoiding and/or controlling for external factors that could heavily contribute to a firm's failure (i.e. financial crisis and the dot-com bubble), would help to distil the risks attached to the innovation activity carried out by firms.

3 Nemet and Johnson (2012) exposed a negative technological impact of inventions drawing from technologies coming from distant areas, particularly in the fields of computers, communications, and electronics. These are deemed the 'systemic' technologies that make up and form part of a broader technological system (Breschi and Malerba, 1997; Marsili, 2001). In general, new inventions that are technologically distant from the prevailing technological system are likely to have a lower (or even an adverse effect on) impact as they will not be compatible.

Existing empirical findings seem to suggests that novelty might play an important role in driving the type of delisting that a firm may experience. Nemet and Johnson (2012) exposes that citing prior art that is technologically nearer has a strong effect on technological value, in terms of forward citations, whilst Cockburn and Wagner (2007) find that firms with higher share of highly cited patents are likely to exit via merger/acquisition. This may indicate that firms involved in the exploitation of familiar technologies which further generate a high number of citations are going to increase the likelihood of exit via merger/acquisition. In contrast, those firms that exploit familiar technologies and that do not subsequently generate highly cited inventions may end up either surviving as Colombelli et al. (2013) suggest, or exiting due to bankruptcy.

Local search can produce novelty as long as familiar components are recombined in novel ways (Arts and Veugelers, 2014). However, local search that does not generates novelty can only incrementally increase the knowledge of a company and hardly represents any form of valuable asset (Ahuja and Lampert, 2001). Therefore, local search that do not produce novelty is expected to increase the likelihood of exit via bankruptcy, in contrast only search in familiar domains that produces technologically novel inventions will increase the probability of a firm survival. This hypothesis may work for those firms that want to endure, whereas a lower survival probability is expected for firms that focus being acquired.

2.3. Firm’s Exit Strategies

This paper brings in theory form the *resource-based view* of the firm, which emphasises that the internal characteristics of the firm contribute to the strategic choices that lead to distinct outcomes (Barney, 1991; Wernerfelt, 1984). The ability of a firm to develop distinct resources and capabilities enhance its ability to adapt to changing competitive environment and improves its survival prospects (Esteve-Pérez and Mañez-Castillejo, 2008). Firms then search for knowledge and technology to increase their likelihood of developing newer capabilities, such as novel inventions, as well as the heterogeneity of their resources. Consequently, firm’s choice of knowledge-search strategy should directly influence their survival rate. A greater stock of accumulated knowledge leads to higher survival rates (Cockburn and Wagner, 2007).

This study also draws from the *industry dynamic* view of the firm, which considers factors inherent to the market environment in which a firm is located, as potential enablers of firm survival. Furthermore, the point in the technology or industry life cycle in which a firm operates is a significant indicator of firm's survival (Agarwal and Gort, 1996; Suarez and Utterback, 1995). Lastly, failure is positively associated with overall industry entry rates and average price cost margins (Audretsch, 1991; Audretsch and Mahmood, 1995). Fama and French (2004) reported a substantial increase in the number of new lists at the NASDAQ between 1973 and 2001, followed by a sharp decline in survival rates over time. Furthermore, they find that firms that survive show higher profitability and growth rates. Moreover, Seguin and Smoller (1997) find that lower priced stocks have a higher mortality rate than high priced issues. Interestingly, market capitalisation does not influence firms' mortality rates. Chava and Jarrow (2004) find little predictive power by accounting variables when market-based measures are already included in the model. In contrast, Beaver et al. (2005) found additional explanatory power of financial information.

Several studies have examined the effect of firm's innovative activities on survival probabilities (Banbury and Mitchell, 1995; Bayus and Agarwal, 2007; Buddelmeyer et al., 2009; Christensen et al., 1998; Colombelli et al., 2013; Colombo and Delmastro, 2001; Doms et al., 1995; Hall, 1986; Perez et al., 2004; Potters, 2011). Most of these studies suggest that innovation should be beneficial for the survival of busnesses, although which exit type is not always identified from prior research. Only recently, a few studies have examined the interlink between innovation and failure by distinguishing different exit types (Cefis and Marsili, 2012, 2011; Fontana and Nesta, 2009; Wagner and Cockburn, 2010). According to prior findings, innovation can influence both survival as well as exit. For example, innovation was found to increase the probability of firm's survival in the manufacturing sector in the Netherlands (Cefis and Marsili, 2012) as well as in the the internet-related industry in the US (Wagner and Cockburn, 2010). However, according to Cefis and Marsili, (2011) innovaton may not improve firms' chances of survival in high-tech industries but only in low-tech industries.

Innovation seems also to increase the probability of firms being acquired. For firms that want to sell out to another firm, capabilities in new product developmnet seems to be perceived as valuable to potential buyers (Cefis and Marsili, 2012). However, the development of new capabilities required for the introduction of new products or processes may not be enough to succeed. Firms may need to focus on radical innovation to differentiate themselves and establish competititive advantage. Indeed, having radical inventions makes firms more likely to being acquired (Wagner and Cockburn, 2010), but this may involve an increased risk in failures and greater uncertainty (Cefis and Marsili, 2011). Furthermore, Wagner and Cockburn (2010) found that firms with a higher stock of patents are less likely to being acquired, which sugests that patenting may be an indication of the choice of the firm to exploit its innovation in the product market and to protect it from imitation, rather than a desire to sell its ideas to potential competitors.

2.4. Exploration and exit via Merger and Acquisition

The the empirical research based on the RBV (Barney, 1991; Grant, 1996; Nelson and Winter, 1977; Teece et al., 2009) emphasised that the knowledge underlying the innovation process is a strategic asset that helps firms to gain a competitive advantage and ultimately to survive. However, this literature does not account for different forms of exit as they identify exit only as the cessation of production activities. For instance, prior research shows that knowledge exploitation[4] increases firm survival, whilst the exploration of distant technologies is associated with firm mortality (Colombelli et al., 2013). Often, however, many businesses are created with the prospect of being sold on to larger firms, or to merge to other firms to stay competitive and to have access to managerial or financial resources. Therefore, the exit though M&A could be a signal of an explicit strategy instead of a failure (Freeman et al., 1983; Headd, 2003). Entrapreneurs may decide to sell their companies in order to reap the rewards from their business activities, or to shift their focus to a new venture (Cefis and Marsili, 2011). For example, venture capitalist when funding new businesses may give constraints on the timing and mode of exit of the firm. In such a situation, the knowledge-search strategy of firms becomes essential to the successful generation of radical inventions and signaling a variety of capabilities.

Therefore, for those firms that want to exit the market through M&A would necessitate to invest heavily in exploration activities to push fast rates of innovation and sell their ideas in the near future. Usually, this strategy comprises small and young firms that have just entered the market. They do not sale and do not have any income, but they take on debt to pursue as much exploration to the point that they sell their inventions. By drastically pursuing explorative knowledge-search they can increase the introduction of

[4] (i.e. with a high level of technological coherence and variety, and a low level of technological distance)

novel products (Katila and Ahuja 2002), boost breakthrough inventions (Ahuja and Lampert, 2001), and have a positive effect on stock market prices (Harrigan and Di Guardo, 2018). All of this can be perceived as valuable to potential buyers. We can state:

H2: Exploration increases exit via Merger and Acquisition

2.5. Exploration and exit via Delisting

In line with the tension view, which asserts that deep knowledge leads to myopia thus suggesting that recombination of distant or diverse knowledge is necessary to generate novel ideas (Taylor and Greve, 2006; Weisberg, 1999), exploring would yet be essential to firm's survival. Distantly derived components are essential for the creation of novel ideas that achieve high economic value (Ahuja and Lampert, 2001). However, prior research denoted that in the fields of computers, communications, and electronics, firms drawing from technologies coming from distant areas achieve a negative impact of invention quality (Nemet and Johnson, 2012). These are deemed the 'systemic' technologies that make up and form part of a broader technological system (Breschi and Malerba, 1997; Marsili, 2001). In general, new inventions that are technologically distant from the prevailing technological system are likely to have a lower impact, or even an adverse effect, as they will not be compatible. Moreover, innovation incorporating external knowledge involves high risk and higher chances of failures (Arts and Veugelers, 2014). Efforts to assimilate external knowledge take investment and considerable amount of time to develop. They also require experties that may not always be available to the firm. Inventors may lack the deep familiarity that they have with more proximate knowledge (Constant II, 1980; Laursen, 2012; Vincenti, 1990), leading to potential negative outcomes. For example, prolonged revision and iterations that may eventually extend beyond what a firm or investors may be willing to tolerate.

In general, for those firms that want to endure they might have different options which may be safer than exploring outside their knowledge boundaries. Other viable options could be acquiring firms, increase their production efficiency, exploit potential economy of scales that could lead to a more competitive prices. Usually, this strategy comprises large and well-established firms with high income and sales. Over time these firms tend to focus primarily on local search (Patel and Pavitt, 1997). All considered, for this type of firms in the ICT sector, we can state:

H2: Exploration increases exit via Delisting

2.6. Exploitation and exit via Merger and Acquisition

A good part of the organisational learning literature suggests that firms should engage with the exploitation rather than the exploration search process (March, 1991). The limited cognitive abilities of employees would restrict the solution of problems to a limited number of solutions, which the majority could be within their knowledge spectrum (Knudsen and Levinthal, 2007). Futhermore, as more knowledge of a specific scientific field is accumulated, the easier the learning related to that knowledge (Constant II, 1980; Laursen, 2012; Vincenti, 1990). Employees initially tend to search for solutions in areas where the firm has already expertise as proximate and familiar knowledge should be easier to learn than distant and unfamiliar one (Cohen and Levinthal, 1990). Prior empirical findings exposed that exploitation increase the introduction of novel products (Katila and Ahuja 2002) as this enables them to make continuous improvements to their existing products, as well as increases the chances of firm's survival (Colombelli et al., 2013). Moreover, those firms looking for a sell off their business may value the firms involved in the exploitation of their extant knowledge and the pursuit of local search activities. Therefore, firms focus on exploitation of familiar knowledge will increase firm's survival as well as the the exit through M&A.

H3: Exploitation decreases exit via Delisting

H4: Exploitation increases exit via Merger and Acquisition

2.7. Technological Novelty and firm Survival

Survival advantage may not only come from reusing familiar technologies, but from several other assets own by resourceful firms. A potential asset is the generation of technological novelty. The literature on technological exposes that novelty is essential for the long term prosperity of the firm (Anderson and Tushman, 1990; Christensen et al., 1996; Henderson, 1990; Rosenkopf and Nerkar, 2001; Utterback, 1994). Several studies empirically demonstrated that technological novelty is associated to higher citations rates as well as radical innovation (Arts et al., 2013; Arts and Veugelers, 2014; Briggs and Buehler, 2018b) and its impact is effective in any industry (Verhoeven et al., 2016). However, Nemet and Johnson (2012) exposed that citations to external prior-art were significantly less important to predicting future citations in the ICT sector. Inventions that cites prior-art from the same technological calss receive higher forward citations, suggesting that novelty must occur within familiar technologies to be successful.

Verhoeven et al., (2016) point out that recombinations using familiar technological classes are very few thus much more sporadical than those using distant technologies. This was further supported by Arts and Veugelers (2014), who exposed that only recombinations of familiar technologies have the higherst potential to become breakthrough innovations but are only a very few in numbers. Moreover, recombinant novelty drastically increases the chances of patenting failures making recombinat novelty extremely risky to pursue particularly in the ICT sector. Thus, we can state:

H5: Technological Novelty increases exit via Delisting

On the other hand, recombinant novelty may be perceived by firms looking to acquire other buinesses as a potential asset, in particular as a way of avoiding carry out risky R&D themselves. Thus, firms may carry on forward an acquisition after a thoughrough check of the novelty is viable for future growth and prosperity. Thus, we could say:

H6: Technological Novelty increases exit via Merger and Acquisition

3. Methodology

3.1. Dataset

This study focuses on the relevance of firms' organisational learning and recombinant novelty for the survival of firms from the ICT sector, to do this it combines data on firm characteristics such as age, financial condition and market environment with detailed information on patenting activity. Patent information included in this research comprises *ex-ante* measures of technological novelty as well as knowledge-search. The most recent version of the NBER patent dataset contains information on patents granted between 1963 and 2006. The data assigned a CUSIP code to each assignee organization by reviewing the variants of assignee names through meticulous examination (Lerner and Seru, 2017). Firm's financial data on a quarterly basis is obtained from the Centre for Research and Security Prices (CRSP) with the Compustat North America merged database.

The sample comprises a section from the population of the Information and Computer Technology (ICT) companies operating in the US. This industrial sector was selected for a number of considerations. First of all, it is a sector with a high number of inventions and with substantial R&D intensity. Second, this sector involves quite an active patenting activity, shown by the number of patents produced each year, as protection from patents can be very important for firm survival (Cockburn and Wagner, 2007). According to a series of prior studies, patents are regarded as a meaningful indicator of innovation in this industry (Appleyard, 1996; Podolny et al., 2007; Yayavaram and Ahuja, 2008).

Table 10: Sample of firms by industry operating between 1980 and 2001

N.	Industry	Operating	Merged/Acquired	Delisted	Total	% Total
1	IT Services	24	51	18	93	0.1
2	Software	47	225	52	324	0.36
3	Communications Equipment	25	79	30	134	0.15
4	Technology Hardware	14	61	34	109	0.12
5	Electronic Equipment	53	72	27	152	0.17
6	Semiconductor Equipment	40	49	11	100	0.11
	Total	**203**	**537**	**172**	**912**	**1.01**

The firm sample is constructed as follows. Financial data for 1,569 firms operating in the US between 1980 and 2000 was obtained from the COMPUSTAT[5] database. Only firms pertaining to the six GIC codes from the IT Services (451020), Software (451030), Communications Equipment (452010), Technology Hardware (452020), Electronic Equipment (452030), and Semiconductor Equipment (453010), are included in the analysis. Since the innovation covariates are considered in lags of a maximum of four years, the sample includes firms with at least 4-year financial data. In a second step, the financial data was merged with the patent data. Patent data is drawn from the newest version of the NBER patent citations database which provides detailed patent related information on around 3.65 million US patents granted between January 1963 and December 2006. The two databases are merged using the firm CUSIP code and patent application date rather than the patent granted date since the latter varies depending on the speed of the patent review process. The final sample comprises of 912 firms and 4,661 firm-year observations from 1980 to 2001. Figure 1 shows the growth in number of firms per industry in the study sample. Most of the industries in the ICT sector (beside from the

5 https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

semiconductor equipment) incurred a decrease in number of firms around the period of the dot-com bubble over the end of the 1990s.

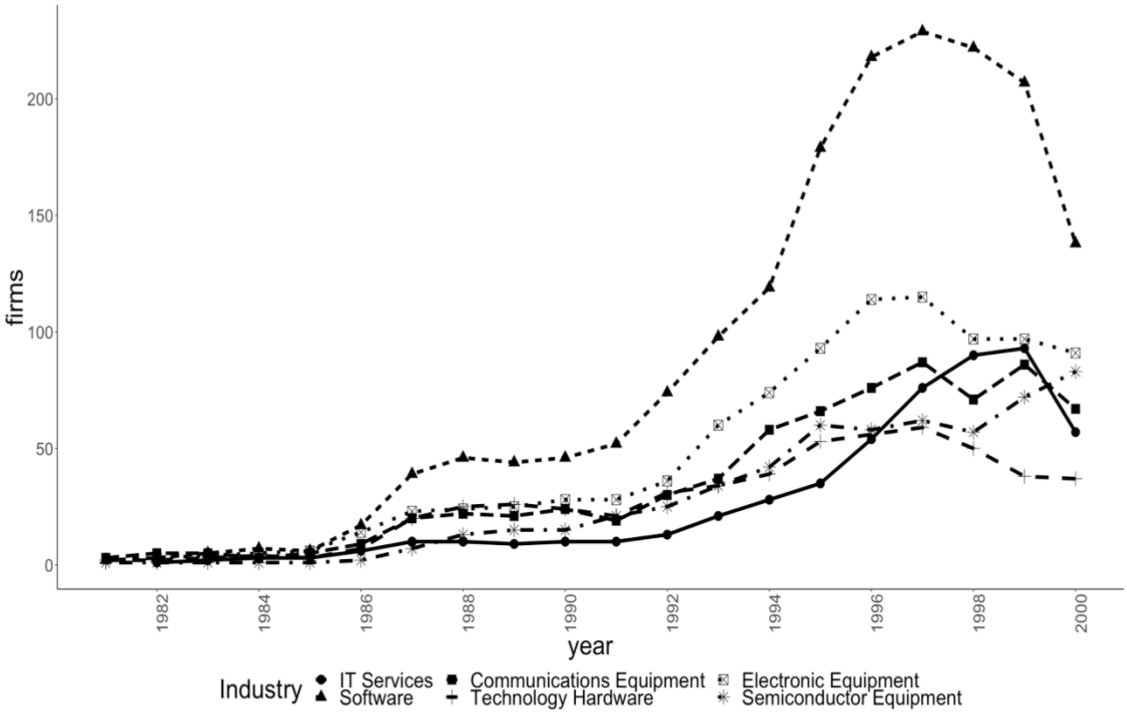

Figure 1: Firm Growth per Year for distinct Industries (Observed Sample)

3.2. Analysis

This study aims to analyse the influence of various firm innovation characteristics on firm survival; thus, a simple multivariate hazard model is adopted with survival time as a nonnegative random variable. Several methodologies have been adopted to empirically estimate the determinants of differential survival rates. Some authors emphasises the advantages of the hazard models in predicting bankruptcy when adopting financial and accounting variables (Chava and Jarrow, 2004; Shumway, 2001), and the estimators of these variables is overshadowed when controlling for external factors suing more traditional dummy estimator models. Therefore, the use of hazard model seems desirable as this analysis uses financial indicators whilst controlling for market-based indicator.

Different survival models are estimated were the hazard function depends on both time-variant regressors x_{it} such as the net income or sales, as well as time-invariant regressors such as firm and patent characteristics x_j. A number of papers focusing on the firm's survival have already adopted the Cox proportional hazard models (Agarwal and

Audretsch, 2001; Audretsch and Mahmood, 1995; Cockburn and Wagner, 2007). More formally, the following Cox proportional hazard equation will be adopted:

$$h_i(t|Delisting_i) = \lambda_0(t)\exp\{Search\ Depth_{t-1} + \beta_1\ Search\ Scope_{t-1} + \beta_2\ Recombinant\ Novelty_{t-1} + \beta_3\ Patents_{t-1} + \beta_k\ Financial\ Variables_{\ it}\} \quad \text{(eq.1)}$$

$$h(t|Merger/Acquisition_i) = \lambda_0(t)\exp\{Search\ Depth_{t-1} + \beta_1\ Search\ Scope_{t-1} + \beta_2\ Recombinant\ Novelty_{t-1} + \beta_3\ Patents_{t-1} + \beta_k\ Financial\ Variables_{\ it}\} \quad \text{(eq.2)}$$

The Cox proportional hazard model is based on several assumptions. A set of tests were carried out to assess the validity of the data. The Schoenfeld residuals to validate the proportional hazard assumption, the Martingale residual to assess nonlinearity, and the deviance residual to examine influential observations. The Schoenfeld residual test reports that neither of the covariates nor the global test (>0,0001) violate the proportionality assumption (see Appendix.1).

3.3. Covariates

3.3.1. Identifying Bankruptcies, Mergers and Acquisitions

Detailed listing information on the NASDAQ stock exchange from the Centre for Research on Security Prices (CRSP) database was obtained for each firm. This data contains not only the date of the IPO for each firm but also information as to whether or not a firm is still listed on the NASDAQ. If trading in a firm's stock was discontinued, the database allows us to distinguish between firms which were delisted due to business failure and firms which merged with other companies. Following prior research, this study document firm's exit trends as Chapter 7 and Chapter 11[6] (Cockburn et al., 2006; Corbae and D'Erasmo, 2017) if the firm-year observation corresponds to the last period

6 In the US a firm can default on its debt, triggering two distinct bankruptcy procedures: *Chapter 7* – liquidation – the firm liquidate its assets at firesale discount, which it uses to pay debts, incurs a bankruptcy cost, and exits; *Chapter 11* – reorganisation – the firm and lenders renegotiate the defaulted debt, bargain over the repayment fraction, the firm pays bankruptcy cost, reduce its debt and faces equity finance costs, debt finance costs, discount in its capital assets, and it is not allowed to pay dividends and continues operating (Corbae and D'Erasmo, 2014).

of the firm in our sample and the firm is identified with the variable DLRSN (Research Company Reason for Deletion) equal to codes 02 (Bankruptcy), 04 (Reverse acquisition), 07 (Other, no longer files with SEC among other possible reasons, but pricing continues) 09 (Now a private company) and 10 (Other, no longer files with SEC among other possible reasons). This study considers firms that exit via merger or acquisition when these are identified with the variable DLRSN coded as 01 (Mergers and acquisitions). The survival time is right-censored at December 2000 as an exit event is not observed for continuing firms, and the sample is truncated as firm observations after exit are not recorded.

3.3.2. Firm's Organisational Learning processes

This study employs the concept of a two-dimensional representation of the firm's search focus (Katila and Ahuja, 2002) of which can vary not just in their *scope* (local versus distant) but in their *depth* defining the degree of reused or exploited knowledge. In this sense, firms can use and reconfigure their existing knowledge repeatedly leading to varying degrees of familiarity. This study builds on this idea and further tries to identify the differences between firms focusing on different levels of the two knowledge-search focuses and their impact on a firm survival. The analysis uses firms' patenting activity and the enclosed information on technological classes to identify the processes of knowledge-search. The more the use of knowledge the more deeply the knowledge is known, therefore, the average number of times a firm repeatedly used the citations in the patents it applied for. The *Search Depth* variable is created by measuring the number of times, on average, that each backward citation in year *t* was repeatedly used in the past five years. The sum of the occurrences was then divided by the total number of previous citations that the firm received over the previous five years. More formally, the search depth of a firm *i* in year *t-1* is calculated as following:

$$Search\ Depth_{it-1} = \frac{\sum_{y=t-6}^{t-2} Repetition\ Count_{iy}}{Total\ Citations_{it-1}} \qquad \text{(eq.3)}$$

The variable *Search Scope* defines knowledge that is explored outside the expert area of the firm. The proportion of previously unused citations in a firm's focal year list of citations. This corresponds to the share of citations in a focal year that were never used in the previous five years by that firm. For example, a firm with ten patents in a given year, each one of them cited 10 other patents. Eight out of ten citations are new to the firm (i.e. they have never been previously cited by the focal firm) resulting in the firm's knowledge search scope of 0.8. Regarding the previously used citations in each patent, one has been used twice whereas the other three times resulting in knowledge-search depth of the firm is 0.5. Thus, the search scope of a firm *i* in year *t-1* is calculated as following:

$$Search\ Scope_{it-1} = \frac{New\ Citations_{it-1}}{Total\ Citations_{it-1}} \quad \text{(eq.4)}$$

3.3.3. Firm's Recombinant Novelty of Inventions

Prior studies adopted a firm's number of patent weighted citations as a measure of patenting quality[7], and reported that firms owning highly cited patents make them more likely to be acquired (Cockburn and Wagner, 2007). In contrast, this study considers the novelty of the searched knowledge using an indicator of novel recombination developed from previous research. For instance, patents comprising technological novelty have been linked to invention quality measures (Arts and Veugelers, 2014) and are expected to decrease the mortality rate of exit via delisting, whilst potentially increasing the chances of exit through merger and acquisition. This measure is constructed by averaging the number of novel subclass pairs by the patent total number of subclass pairs. To construct the firm's level of novel recombination encompassed into knowledge-search, the sum of a firm's yearly patent recombinant novelty was adopted. However, other variables describing a firm's patent portfolio such as the number of patents (*Patents*), and the number of patent weighted citations (*PatW*) were further considered in this research. Consequently, the novelty of a firm *i* in year *t-1* is calculated as following:

[7] Pioneering studies from the Economics of Innovation literature revealed that patent citations are a direct proxy of a firm's technological importance (Narin et al., 1987; Trajtenberg, 1990). Trough surveys and peer expert reviews, these studies exposed that on average being highly cited represent cutting-edge technology and the relationship is particularly strong for a restrictive group of patents having the highest number of forward citations in a particular field (Achilladelis et al., 1990; Harhoff et al., 1997).

$$Recombinant\ Novelty_{it-1} = \sum \frac{First\ time\ Technological\ Class\ Combination_{it-1}}{Total\ Number\ of\ Technological\ Classes_{\ it-1}} \quad \text{(eq.5)}$$

By introducing the search for originality as a distinct dimension, even within local domain a search that targets original knowledge can be highly explorative. As such, knowledge that recombines prior knowledge in a novel way can be regarded as original. Thus, multiple interaction terms between the knowledge-search processes and the recombinant novelty indicator are further examined to identify the whether the novelty increases the performance of one or the other knowledge-search process.

3.2.4. Market and other Firm Characteristics:

Firm's *Age* is measured as the difference between the initial public offering (IPO) which is the date of legal incorporation and the first recorded year of observation in the dataset. Following prior research (Cockburn and Wagner, 2007), this study controls for external market environment by including the average value of the NASDAQ Composite Index in the year prior to the year in which a firm's IPO took place (*Nasdaq Index*). The time period of analysis is believed to have experienced high market volatility caused by the investors eager to raise large amount of capital at remarkably low prices and without much inspection. Furthermore, financial data on a quarterly basis comprising a firm's net income (*Net Income*) and net sales (*Net Sales*) are treated as time-varying coefficients in the multivariate survival analysis.

4. Results

4.1. Summary Statistics

Table 12 reports the descriptive statistics for all the covariates used for the regression analysis by comparing firms with at least one patent (*Inventor*) from those firms with no patents (*No-Inventor*) over the full length of the study. No-Inventors show no statistic for patenting information, whereas comparison of innovation is assessed for Inventors only. One-year lag covariates are used for the innovation covariates. For the semi-parametric models, in the next section, the one- and two-year lags are adopted as a rapid exit is expected from those firms that may want to be acquired after they developed novel products. However, other lags such as three- and four-year are also investigated.

Table 12 also shows that firms that filed for delisting tend to focus on exploration rather than exploitation knowledge-search. They have a much lower average value of search depth than the total average, and their average search scope is much higher than the one from firms with that exited due to merger/acquisition or that are still operating. Furthermore, on average, bankrupted firms tend show on average higher levels of recombinant novelty, although the average number of patents is lower than the total average. In line with prior findings, firms that went bankrupt are younger than the average age of the sample, whilst firms that survive are much older in general. Consequently, firms that exited due to delisting are in general younger firms born in moments of lower market valuation that focus on exploring new unfamiliar knowledge and generate a small number of highly novel inventions. In contrast, still operating firms are older firms born in periods of high market valuation that focus mainly on exploiting their familiar knowledge and produce a large number of patents with little novelty on average.

Table 11 shows significant differences among the three groups means at better than the 1% level. Furthermore, the Turkey HSD test shows that there is statistically significant difference between individual pair of groups at the 5% level. Only Depth is not statistically different between M&A and Operating firms, and the stock of patents between M&A and Delisted.

Table 11: ANOVA and Post Hoc Test with Turkey Honest Significant Differences

		ANOVA	M&A-Deleted	M&A-Operating	Deleted-Operating
1	Depth	0.0000	4.5330*	1.7131	6.2461*
2	Scope	0.0000	16.0040*	10.3519*	26.3560*
3	Novelty	0.0000	11.1926*	5.7367*	16.9293*
4	Patents	0.0000	2.6931	9.1024*	11.7955*
5	Age	0.0000	114.1076*	36.7619*	150.8695*
6	Sales	0.0000	13.4630*	6.5428*	20.0059*
7	Income	0.0000	17.6747*	11.5087*	29.1834*
8	NasdaqIndex	0.0000	23.0993*	19.1323*	42.2316*

studentized range critical value (.05, 3, 4658) = 3.3155793

Table 12: Summary Statistics of Distinct Survival Groups

		Merger/Acquisition				Delisted				Operating				Total			
Inventor	Variable	Mean	St	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Yes	Depth	0.44	0.57	0.00	3.46	0.23	0.32	0.00	1.49	0.58	0.62	0.00	2.99	0.46	0.57	0.00	3.46
	Scope	0.51	0.21	0.00	0.69	0.58	0.17	0.10	0.69	0.48	0.19	0.00	0.69	0.51	0.20	0.00	0.69
	Novelty	0.20	0.23	0.00	0.69	0.27	0.24	0.00	0.69	0.17	0.22	0.00	0.69	0.20	0.23	0.00	0.69
	Patents	1.62	1.02	0.69	7.44	1.48	1.33	0.69	6.29	2.07	1.25	0.69	6.45	1.73	1.14	0.69	7.44
	Age	0.21	0.69	0.00	3.47	0.12	0.44	0.00	2.83	0.25	0.79	0.00	3.26	0.22	0.71	0.00	3.47
	Sales	3.56	1.35	0.00	8.96	3.19	2.17	0.00	10.35	3.75	1.53	0.06	8.46	3.58	1.49	0.00	10.35
	Income	1.36	1.33	-6.10	7.09	0.94	1.89	-4.71	7.09	1.64	1.67	-6.40	6.50	1.40	1.50	-6.40	7.09
	Nasdaq-Index	6.46	0.47	5.69	8.00	6.40	0.45	5.69	8.00	6.50	0.46	5.69	8.00	6.46	0.47	5.69	8.00
No	Depth	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Scope	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Novelty	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Patents	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Age	0.18	0.54	0.00	2.56	0.12	0.40	0.00	2.83	0.26	0.64	0.00	3.26	0.19	0.54	0.00	3.26
	Sales	2.62	1.21	0.00	8.95	1.91	1.40	0.00	7.67	2.93	1.60	0.00	8.98	2.54	1.39	0.00	8.98
	Income	0.55	1.04	-6.35	4.43	-0.07	1.10	-6.35	3.44	0.86	1.29	-2.76	6.30	0.49	1.16	-6.35	6.30
	Nasdaq-Index	6.38	0.42	5.69	8.00	6.30	0.41	5.69	7.30	6.44	0.41	5.69	8.00	6.37	0.42	5.69	8.00

Note: all covariates are in logarithmic form

Looking at firms that exited via merger/acquisition show that this group tends to focus on exploration whilst still carrying out substantial exploitation activity of familiar knowledge, as they show a higher search scope and a significantly lower search depth than operating firms. The above findings are in line with prior research that demonstrated that firms at the beginning of their technological trajectory are likely to move into uncertain environments to acquire distantly sourced technologies with high potential for recombinations. This post entry performance of firms involves high levels of turbulence which can drastically decrease the likelihood of survival rate (Colombelli et al., 2013). Further supporting this view, (recombinant) novelty is positively correlated with search scope indicating that exploring new knowledge increases the variety of knowledge and consequently the recombinatory potential of innovation which is in line with the tension view of knowledge-search (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Lazonick, 2005; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008). Interestingly, search scope seems to have a higher positive correlation with net income and net sales than search depth. Search depth is substantially positively correlated with the number of patents, as is search scope although to a lesser extent. Search depth is low and negatively correlated with age, whilst it is positively correlated with net sales and net income.

Table 13: Pearson Correlation

	1	**2**	**3**	**4**	**5**	**6**	**7**
Depth							
Scope	0.21*						
Novelty	0.25*	0.56*					
Patents	0.71*	0.62*	0.41*				
Sales	0.23*	0.28*	0.17*	0.45*			
Income	0.24*	0.27*	0.15*	0.44*	0.75*		
Age	-0.05*	0.06*	0.05*	0.03	0.02	0.02	
Nasdaq-Index	0.06*	0.07*	0.02	0.09*	0.13*	0.06*	-0.09*

Note: *p<0.01

4.2. Non-Parametric Analysis

The involvement of innovating firms in knowledge-search processes is initially analysed by comparing the survival curves between firms that exited via delisted from those that exited via merger/acquisition (Figure 2). The Kaplan-Meier non-parametric estimator is used to estimate the survival function (eq.6) from the sample data (Kaplan and Meier, 1958).

$$\hat{S}(t) = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i} \qquad \text{(eq.6)}$$

The function includes n_i the number of firms that are still at risk at time t_i, and d_i the number firms that exited at time t_i. The product is over all observed exit times that are less than or equal to t. The results are usually displayed as a Kaplan-Meier curve, where survival rate is plotted against duration. The study starts at time 0 with the survival probability at 1.0. Every time a firm experience an event, in this case exit via delisting or merger/acquisition, the survival probability drops by some percentage of the curve which is equal to the number of firms that experienced the events divided by the number at risk.

The knowledge-search processes are transformed into discrete groups by separating firms-year observations with a value of zero as low-level from high-level of knowledge-search[8]. The graph shows that firms with high levels of both search scope and search depth (see also Appendix.2) have higher survival rates than those firms with low levels of knowledge-search. Although, this is only true for exit via delisting/bankruptcy (left graph).

[8] The maximally selected rank statistics method to determine the optimal cut-point for continuous variables was also explored. Search depth was thus considered high when its value is higher than 0.59, whereas for search scope this value was 0.65. Similar results were obtained for the Kaplan-Meier Survival curve, both knowledge-search processes increase the survival rates of firm exit via delisting.

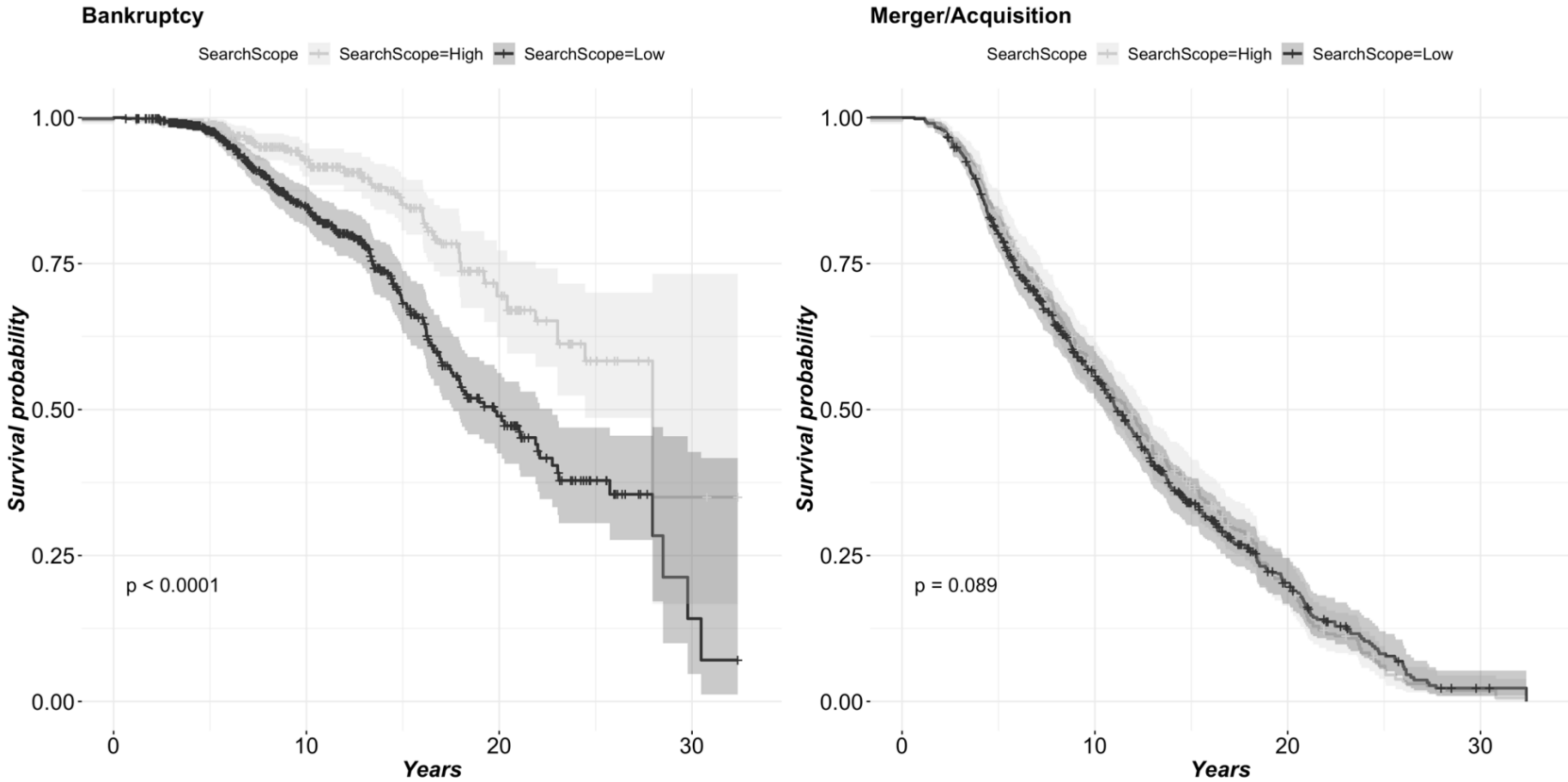

Figure 2: Comparison of Kaplan-Meier Survival Curves between Firm Exit via Delisting and Merger/Acquisition

4.2. Survival Analysis

This section reports the empirical account of the relationship between firms' characteristics and firm survival: the parametric survival model with a set of firm-specific covariates. The covariates represent the information regarding the innovation activity such as the search processes carried out by firms, and the novelty of their inventions. This is accomplished by distinguishing between firms that exited due to delisting from those that exited via merger or acquisition. Furthermore, this approach adopts lagged innovation variables to account for the rapid strategic changes in firm's patenting behaviour that may occur in response to market changes, for instance periods of intense growth in the ICT sector (Cockburn and Wagner, 2007), in which innovation was most radical (e.g. between 1989-1997; Mazzucato and Tancioni, 2008). In contrast, using an average value between several years of knowledge-search indicators may fail to capture the dynamic response of firms to the market changes.

Table 14 below, reports the Cox proportional hazard regression results with dependent variable as the elapsed time between a firm IPO year and the moment of exit. The first specification in Model 1 contains only the financial variables for exit via delisting and Model 6 for exit via merger or acquisition. The other models introduce the innovation covariates in lagged form, Model 2 and Model 7 the one-year lagged whilst Model 4 and Model 9 the two-year lagged covariates respectively. Every model includes dummies for every industrial sector (Industry Dummy) as well as a dummy to control for firms involved with the innovation activity (Inventor Dummy).

Table 14: Cox Proportional Hazard Regression Results on Exit via Delisting and M&A

	Delisting					Merger/Acquisition				
		lag1	lag1	lag2	lag2		lag1	lag1	lag2	lag2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Search Depth		-2.566**	-1.993*	-2.681**	-1.847+		0.337+	0.505*	0.399+	0.456+
		(0.808)	(0.882)	(0.943)	(1.039)		(0.198)	(0.251)	(0.210)	(0.257)
Search Scope		-2.552**	-2.666**	-1.359+	-1.366+		0.413	0.549	1.019***	1.017**
		(0.913)	(0.956)	(0.785)	(0.789)		(0.341)	(0.339)	(0.301)	(0.310)
DepthxScope			-3.336		-3.981			-1.721+		-0.222
			(3.611)		(3.799)			(1.033)		(0.991)
Recombinant Novelty		2.108+	-1.774	-1.612	2.600		-0.693	0.781	0.252	0.599
		(1.101)	(3.466)	(1.422)	(8.659)		(0.493)	(1.156)	(0.376)	(1.388)
Patents		1.004***	1.148***	1.151***	1.253***		-0.199+	-0.119	-0.198+	-0.194+
		(0.230)	(0.261)	(0.229)	(0.253)		(0.102)	(0.111)	(0.103)	(0.109)
Inventor		-0.331	-0.274	-0.428	-0.415		-0.106	-0.133	-0.372*	-0.372*
		(0.421)	(0.416)	(0.417)	(0.413)		(0.171)	(0.172)	(0.162)	(0.162)
Net Sales	-0.557***	-0.583***	-0.582***	-0.593***	-0.600***	0.089+	0.122*	0.121*	0.119*	0.119*
	(0.109)	(0.115)	(0.116)	(0.115)	(0.115)	(0.053)	(0.056)	(0.056)	(0.056)	(0.056)
Net Income	-0.219*	-0.241*	-0.256*	-0.258*	-0.246*	-0.098+	-0.085	-0.081	-0.099+	-0.099+
	(0.101)	(0.099)	(0.102)	(0.105)	(0.104)	(0.051)	(0.053)	(0.053)	(0.053)	(0.053)
Age	-0.202	-0.275	-0.283	-0.230	-0.238	-0.084	-0.063	-0.074	-0.069	-0.072
	(0.287)	(0.290)	(0.292)	(0.285)	(0.286)	(0.148)	(0.148)	(0.149)	(0.150)	(0.150)
Nasdaq Index	-0.694*	-0.711**	-0.725**	-0.687*	-0.702*	-0.098	-0.064	-0.073	-0.086	-0.086
	(0.274)	(0.272)	(0.272)	(0.273)	(0.274)	(0.121)	(0.124)	(0.124)	(0.123)	(0.124)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,661	4,661	4,661	4,661	4,661	4,661	4,661	4,661	4,661	4,661
R2	0.019	0.023	0.023	0.023	0.024	0.010	0.012	0.013	0.013	0.014
Max. Possible R2	0.192	0.192	0.192	0.192	0.192	0.564	0.564	0.564	0.564	0.564
Log Likelihood	-452.705	-442.917	-441.526	-441.382	-440.698	-1,909.379	-1,905.308	-1,903.014	-1,900.808	-1,900.715
Wald Test	74.560***	86.960***	89.140***	88.160***	87.640***	45.540***	51.680***	55.220***	62.890***	63.050***
LR Test	88.025***	107.601***	110.383***	110.671***	112.040***	46.049***	54.190***	58.779***	63.191***	63.377***
Score (Logrank) Test	80.305***	97.309***	100.302***	99.420***	100.347***	47.373***	53.726***	57.533***	64.952***	65.171***

Note: Cross-section dimension (firms): 912

+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

This approach shows the striking discrepancies in the innovation and the organisational knowledge-search behaviour between firms that exited via delisting and firms that exited via merger and acquisition. Model 2 shows that both the one-year lagged search depth and search scope estimators are negative, strong and significant indicating that both knowledge-search processes decrease a firm risk of delisting. In contrast, both knowledge-search processes increase the likelihood of exiting via merger/acquisition as the search depth and the search scope estimators are positive in both the one- and two-year lagged covariates, although only the two-year lagged search scope is significant. This finding shows clearly that the distinction between firms that exited due to delisting from firms that exited via merger or acquisition provides contrasting results of the effect of a firm knowledge-search behaviour.

The recombinant novelty estimator is strong positive and significant for exit via delisting, although this becomes insignificant after the introduction of the interaction term between search depth and search scope, and insignificant in the second-year lag. Similarly, there is no significant effect of recombinant novelty on the likelihood of exit via merger/acquisition. Although, this finding does not further highlight the beneficial implication of distinguishing between delisting types, this may give interesting insights into the risks associated with novelty which is further discussed in the next section.

5. Discussion

The results from the empirical analysis support the previously advanced hypothesis, suggesting that firm involved in the exploitation of familiar knowledge decrease their likelihood of failure. This result is in line with the prior work suggesting that the generation of knowledge and the introduction of innovation are the results of cumulative patterns, learning dynamics and path dependence (Colombelli et al., 2013). However, the exploitation process also increases firm exit via merger or acquisition. This result further suggests that firms that intend to survive by investing in knowledge-search may want to increase both their explorative as well as exploitative capabilities and doing both at the same time substantially decreases the chances of exit via merger or acquisition. On the other hand, those firms with the intention to sell their assets may gain bargaining leverage from their processes of exploratory search previously carried out, as this has a substantial positive effect on the likelihood of exit via merger or acquisition. Yet potential acquires value the firm with exploitation capabilities as the search depth estimator is positive and significant on the effect of exit via merger/acquisition.

Firms that carry out exploratory search processes also decrease their likelihood of failure, as search scope estimator is negative on exit via delisting. This result is in line with the tension view, which states that exploring unfamiliar knowledge increases the variety of knowledge and consequently the recombinatory potential of innovation (Cohen and Malerba, 2001; Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen and Salter, 2006; Lazonick, 2005; March, 1991; Metcalfe, 1994; Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008) as well as prior empirical findings on firm survival (Colombelli et al., 2013). Furthermore, the analysis shows that potential acquires may consider firm owning unfamiliar knowledge as a particularly valuable asset.

In line with the organisational learning literature, firms should balance the exploration of new possibilities with the exploitation of their existing competences through processes of 'ambidexterity' (March, 1991; O'Reilly III and Tushman, 2004). Firms focusing simultaneously on both exploration and exploitation show particularly advantageous positions, as this seems to drastically reduce the likelihood of exit via both delisting and merger or acquisition. The positive effect is stronger when the three-year lag value is considered (Table 16 in Appendix.3) indicating that an enduring balance has a long-lasting positive effect.

As recombinant novelty was found to be linked to breakthrough and more useful inventions on average (Arts and Veugelers, 2014), this study adopts this *ex-ante* indicator to control for invention quality. The results suggest that firms that generate novel inventions increase their likelihood of failure, as recombinant novelty estimator has a positive and significant impact on exit via delisting. The same strong positive effect is found in prior lags too (Appendix.3), which strongly suggests that novel inventions rise the risks of failure. In contrast, no impact of recombinant novelty on exit via merger or acquisition. The results complement prior findings indicating that firms owning highly cited patents make them more likely to be acquired (Cockburn and Wagner, 2007; Helmers and Rogers, 2010), and further suggest that firms that produce novel inventions which are technological impact they will be more likely to exit via merger/acquisition.

On the other hand, firms generating novel inventions that are not subsequently highly cited substantially increase a firm risk failure. This is a striking example of the binomial nature of novelty as both the saviour and villain (Benner and Tushman, 2003; Rosenkopf and Mcgrath, 2011).

Those firms involved in the patenting activity (Innovators) have a lower likelihood of exit via both delisting and merger or acquisition, although only the latter is significant. This supports prior research that found that patenting is associated with longer survival times (Cockburn and Wagner, 2007). However, a firm's yearly stock of patents significantly increases the hazard ratio of going bankrupt as the patents estimator is positive and significant for both the one- and two-year lagged estimators. Similarly, the yearly number of patent weighted citations has a positive effect on exit via delisting (result not shown). On the other hand, a firm's yearly stock of both the one- and two-year lagged patent estimators are negative, but not significant for exit via merger/acquisition. The results seem to complement Cockburn and Wagner (2007), whilst their models do not capture any significant impact on the likelihood of firm exiting via delisting, they do identify a marginally positive and significant effect of having a portfolio with highly cited patents on the likelihood of exiting via merger/acquisition. This could be due to the total number of firms exiting via merger/acquisition in the years during the boom of the dot-com bubble (1998-2001) is much higher than the number of firms that exited via delisting, which may overshadow the results (see Figure 3 in Appendix 4)

As expected, Model 1 in Table 14 shows that the time-variant covariates net income and net sales drastically decrease the exit via delisting as their estimators are strong and negative. Total assets is also significant whereas the significance of net sales loses significance after total assets is introduced into the model (not shown in the table). Interestingly, net sales increases the probability of exit via merger/acquisition as its estimator is positive and statistically significant, suggesting that strong returns on net sales may be regarded as a valuable asset by acquiring firms. The NASDAQ Index at the time of a firm's IPO covariates estimator coefficient shows a strong, negative and significant effect on firm's mortality, indicating that firms that went public during periods of higher market valuations have higher survival chances.

A number of limitations may be noted. Firstly, this study focused on knowledge-search capabilities and patenting activity, but there may be many more innovating activities that are not captured by patenting that may be relevant for firm survival and competitiveness (e.g. network alliances, reputation, venture-capital backing, talented workers, product categories, tacit knowledge). Secondly, this study considers only publicly traded firms, whereas the results of this analysis might not apply to private companies which are not included since there are no publicly available observations for bankruptcies, mergers and acquisitions. This study does not take into account firms that disappear from the sample without necessarily being bankrupted or exit via merger/acquisitions. Another issue arises when including firms after December 2000, the survival analysis shows same results but with less significant covariates estimators, although they return significant after including considering observations up to 2005. This could be due to the upsurge in merger/acquisition at the end of 1990s and beginning of 2000s.

The results from the Cox models show that the stock of patents increases the risk of delisting, which is in contrast to the prior findings. (Wagner and Cockburn, 2010) and (Cefis and Marsili, 2012) found that the total number of patent applications filed at the USPTO influences significantly firm's survival. (Cefis and Marsili, 2011) found that patenting (dummy variable) does not have an effect on the probability of exit via delisting. In contrast to prior research, the constructed methodological approach separates the quality from the quantity of patents. The correlation table shows that the average firm's patent quality is only moderately correlated with the stock of patents (45%). In this particular sample of firms, holding a large number of patents do not necessarily lead to many valuable patents. This is also emphasised by the peculiar behaviour of ICT firms of buying large quantities of patents for strategic purposes. Contrary to the shared expectation, the result shows that a firm's stock of patents does not increase its survival rate, instead it increases the chances of exit via delisting. Thus, it is plausible that those firms that bought a large number of patents with little quality, had reduced financial resources to survive through the dotcom crisis

6. Conclusion

This study analyses the impact of firm search processes and novelty generation on firm survival. Prior studies highlighted that innovation plays an important role in shaping the likelihood of firm survival (Cockburn and Wagner, 2007; Helmers and Rogers, 2010), although much of the content of patent has not been fully captured. Furthermore, existing studies around firm survival neglect the potential effect of knowledge search, whilst those that do so fail to consider the distinction between distinct delisting types, or do not control for external factors effecting firm survival. This study proposes to deeper the understanding of the impact of firms' innovation activities, such as patenting, the generation of novelty, and the processes of knowledge-search on firm survival. It does that by further distinguishing between firms that exit via delisting from merger/acquisition, and further distil the impact of innovation activities from external effects. The results from the analysis of 911 American firms in the ICT sector over 20 years show that firms that are involved in processes of knowledge-search decrease their likelihood of failure, whilst they are still prone to exit via merger/acquisition. Moreover, firms that generate technological novelty substantially increase their chances of failure.

This study contributes to a number of existing literatures. Firstly, this study contributes to the literature on survival analysis by highlighting the importance of the distinction between distinct exit procedures. Since exit of the firm does not correspond necessarily to the business closure, but business activity can indeed be competitive and just be taken over by another firm. In this way not only different impact of innovation are reported but also distinct firm strategies can be probed. Secondly, this study contributes to the literature on technological novelty by empirically demonstrating the binomial nature of technological novelty. Firms involved in the recombinatory process for the generation of novelty substantially increase their likelihood of failures and although these maybe technologically important (i.e. in terms of receiving number of forward citations), a firm is not less prone to failure. Lastly, this study contributes to the organisational learning literature by further increasing the evidence that a balance between distinct search processes is desirable the health of an organisation.

Appendices

Appendix.1 Schoenfeld test

Table 15: Schoenfeld Test for the Proportional-Hazards Assumption

	Delisting			Merged-Acquired		
	rho	**chisq**	**p**	**rho.1**	**chisq.1**	**p.1**
Depth	-0.0531314	0.2328303	0.6294331	0.0274681	0.2993485	0.5842911
Scope	-0.0237368	0.1171024	0.7321987	0.1453005	8.4902472	0.0035706
Novelty	0.0707059	0.4683230	0.4937597	-0.0137292	0.0796580	0.7777615
PatW	0.0156620	0.0426511	0.8363836	-0.0057280	0.0134480	0.9076798
Sales	0.2029418	6.4989323	0.0107939	0.0229512	0.1765180	0.6743829
Income	0.0457951	0.2269815	0.6337711	0.0085035	0.0242719	0.8761951
Age	0.0721975	0.4644288	0.4955614	-0.0469397	0.9619737	0.3266901
NasdaqIndex	0.0764998	0.6689638	0.4134131	0.0860409	2.9098972	0.0880375
GLOBAL	NA	14.5722428	0.0680164	NA	23.6618039	0.0026108

Appendix.2 Kaplan-Meier Survival Curve

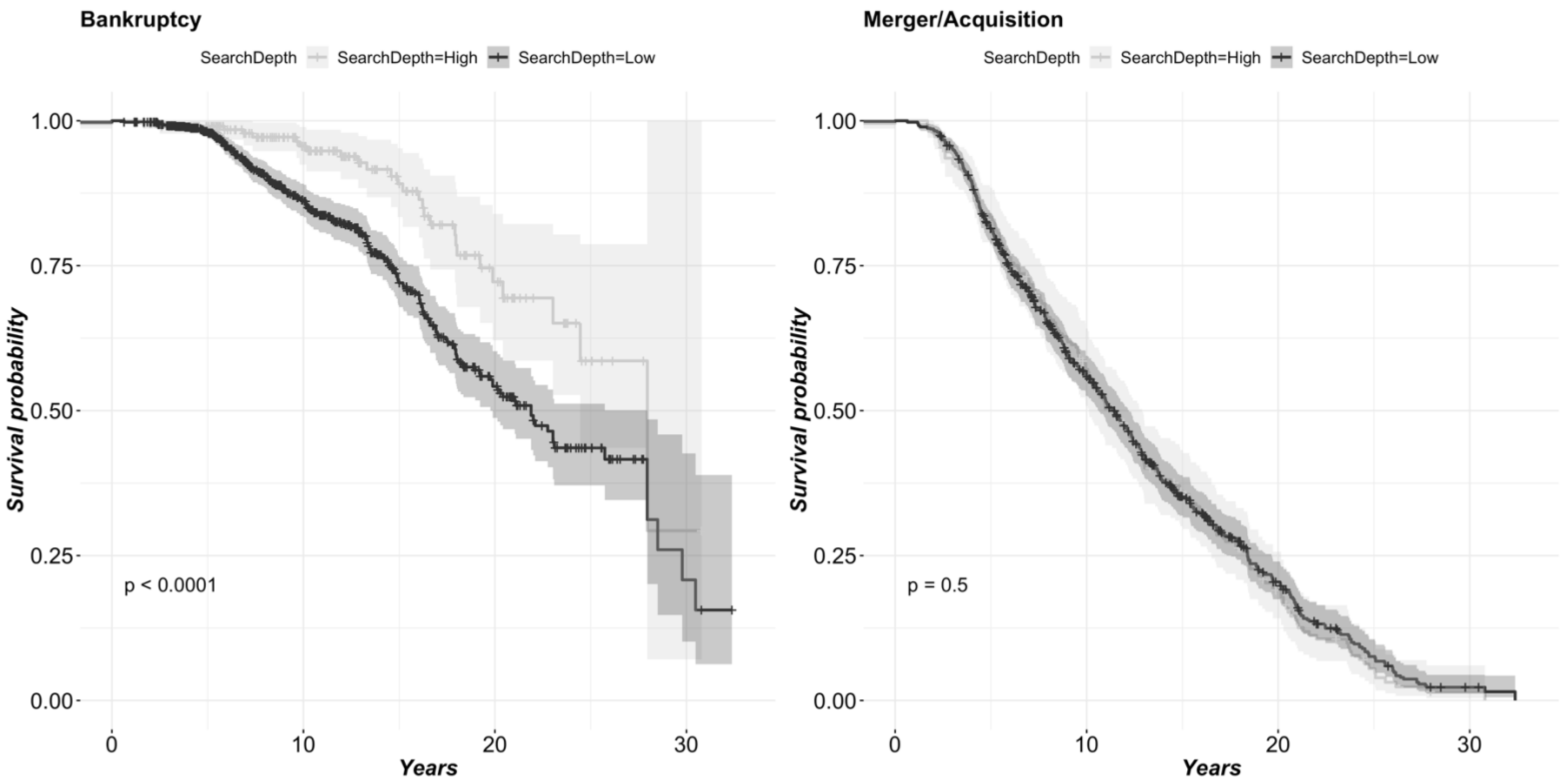

Figure 3: Survival Function Comparison of Depth between Firm Exit via Delisting and M&A

Appendix.3 Cox Proportional Hazard Model

Table 16: Results from the Cox Proportional Hazard Models on Exit via Delisting and M&A

	Delisting					Merger & Acquisition				
		lag3	lag3	lag4	lag4		lag3	lag3	lag4	lag4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Search Depth		-3.754***	-2.537+	-2.660**	-4.422		0.200	0.434	0.463+	0.487
		(1.136)	(1.340)	(1.010)	(3.107)		(0.230)	(0.290)	(0.262)	(0.354)
Search Scope		-3.120**	-3.289**	-1.590+	-1.499		0.764*	0.797*	1.037**	1.027**
		(0.959)	(1.109)	(0.890)	(0.918)		(0.314)	(0.317)	(0.327)	(0.331)
DepthxScope			-10.294*		4.885			-1.995+		-0.961
			(5.112)		(7.394)			(1.121)		(1.252)
Recombinant Novelty		3.590**	2.928	1.903+	1.724		-0.075	-0.566	-0.238	-1.441
		(1.170)	(1.830)	(1.072)	(4.660)		(0.402)	(1.204)	(0.380)	(1.238)
Patents		0.945***	1.206***	0.905**	0.825**		-0.120	-0.050	-0.219+	-0.155
		(0.251)	(0.288)	(0.279)	(0.302)		(0.108)	(0.113)	(0.128)	(0.138)
Non-Innovators		0.331	0.281	0.518	0.524		0.284+	0.268+	0.317*	0.307+
		(0.366)	(0.368)	(0.369)	(0.371)		(0.158)	(0.158)	(0.156)	(0.157)
Net Sales	-0.557***	-0.579***	-0.576***	-0.567***	-0.568***	0.089+	0.100+	0.098+	0.108*	0.105+
	(0.109)	(0.114)	(0.114)	(0.112)	(0.113)	(0.053)	(0.055)	(0.055)	(0.055)	(0.055)
Net Income	-0.219*	-0.181+	-0.189+	-0.229*	-0.233*	-0.098+	-0.091+	-0.088+	-0.097+	-0.093+
	(0.101)	(0.102)	(0.108)	(0.102)	(0.103)	(0.051)	(0.052)	(0.052)	(0.051)	(0.052)
Age	-0.202	-0.222	-0.209	-0.240	-0.246	-0.084	-0.100	-0.091	-0.096	-0.088
	(0.287)	(0.287)	(0.287)	(0.287)	(0.286)	(0.148)	(0.148)	(0.147)	(0.150)	(0.149)
Nasdaq Index	-0.694*	-0.710**	-0.730**	-0.653*	-0.648*	-0.098	-0.095	-0.098	-0.096	-0.101
	(0.274)	(0.272)	(0.272)	(0.272)	(0.272)	(0.121)	(0.124)	(0.124)	(0.123)	(0.122)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,655	4,655	4,655	4,655	4,655	4,655	4,655	4,655	4,655	4,655
R_2	0.019	0.024	0.025	0.022	0.022	0.010	0.012	0.012	0.012	0.013
Max. Possible R_2	0.192	0.192	0.192	0.192	0.192	0.564	0.564	0.564	0.564	0.564
Log Likelihood	-452.705	-439.514	-437.407	-445.422	-445.148	-1,909.359	-1,905.392	-1,903.327	-1,903.392	-1,901.760
Wald Test	74.560***	92.330***	91.410***	82.230***	81.440***	45.550***	53.980***	58.050***	57.550***	61.100***
LR Test	88.023***	114.405***	118.619***	102.589***	103.137***	46.059***	53.993***	58.124***	57.993***	61.256***
Score (Logrank) Test	80.302***	99.065***	100.697***	91.060***	91.193***	47.384***	55.809***	59.945***	59.373***	63.189***

Note: Cross-section dimension (firms): 912

+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Appendix.4 Firm exit via Delisting or Merger/Acquiring

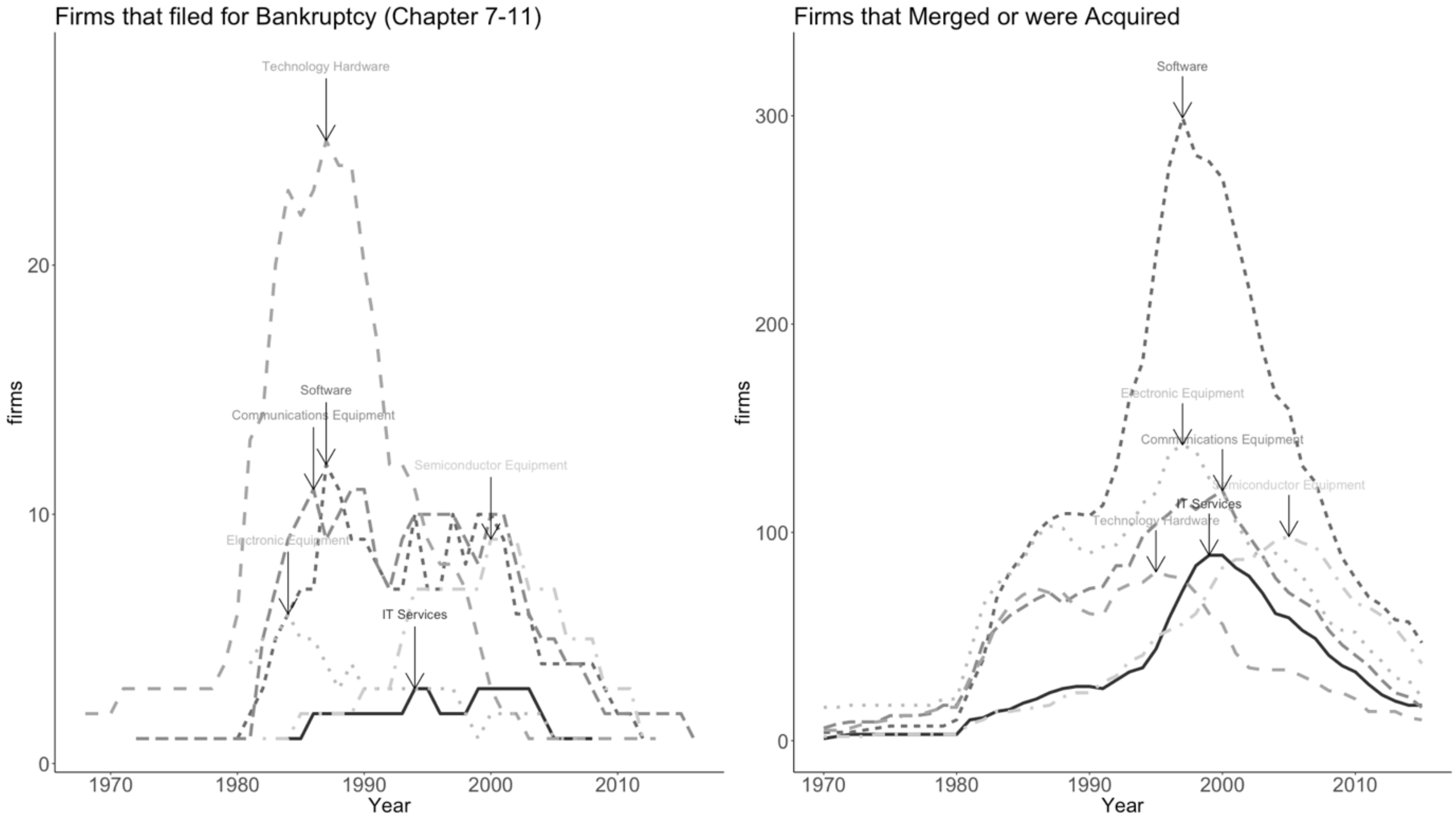

Figure 4: Number of Firms that Exited via Delisting Compared to Exit via M&A

Chapter IV

COGNITIVE NOVELTY, KNOWLEDGE DISSIMILARITY AND BREAKTHROUGH INNOVATION

1. Introduction

Scholars from the innovation studies have been continuously in search for mechanism that could characterise what accounts for significant innovative progress. Patents are ways of tracking inventions and some researchers (e.g. Dahlin and Behrens, 2005; Fleming, 2001) try to characterise the significance of inventions through the analysis of their technological classes. However, those classes might present a limit on the scope of what can be classified as they usually do not capture all the aspects of the novelty attached to a new discovery. (Kuhn, 1962: 62) arguments that scientific ideas are embedded in vocabularies and, in this paper, we will try and develop indicators that do not rely exclusively on technological classes but take into account textual information too.

Few studies employing text mining approaches explored and found a link between novelty and semantic dissimilarity (Gerken and Moehrle, 2012), and further exposed the link between cognitive novel ideas and higher citation rates (Kaplan and Vakili, 2015). Yet not much is known on the textual characteristics of breakthrough innovation. As such, do they build on from the cognitive knowledge presented in their prior citations? Do they represent a radical shift in the language from a given area of knowledge? Do they encompass more cognitive novelty on average than incremental inventions? Furthermore, how long does it take for a breakthrough to occur after the discovery of a particular area of knowledge?

This study endeavours to answer these questions by analysing the similarity of text between patents from the biotech industry to assess the potential of an invention becoming a breakthrough. This study draws on Kuhn's (1962/1996) argument that scientific ideas are embedded in vocabularies, and that shifts in ideas can be detected by shifts in language (Kaplan and Vakili, 2015). Two indicators will be proposed to assess novel ideas as shifts in language. The first indicator assesses the similarity of text between a patent and its prior art citations using a text matching technique, whilst the second indicator considers the similarity of text between a patent and its area of knowledge using topic modelling (Blei et al., 2003). The results suggest that breakthrough inventions are particularly dissimilar from their prior citations, suggesting that they introduce a shift in language from prior art knowledge. This shift reinforces the existing knowledge around a given area (topic) instead of contributing to the generation of a new one.

This paper contributes to the literature on technological novelty, as it introduces two cognitive novelty indicators and compare them to technological novelty indicators. Doing this shows that the textual content in patents gives contrasting information shown by the technological classes. Furthermore, this paper contributes to the literature of breakthrough innovation, as it explores the cognitive aspect of breakthrough inventions using the two proposed indicators. The remainder of this paper proceeds as follows. In Section 2, prior study's findings from the field of strategy and innovation are presented. Section 3 briefly describes the dataset used in the analysis, comprising patent data in the whole biotechnology industry between 1976 and 2001. In Section 4, results are presented from the multivariate probit and logit models for the analysis of the effect of text similarity on breakthrough innovation. Finally, Section 5 concludes and offers some implications for the findings.

2. Background

Breakthrough inventions are typically defined as technologically important inventions having an impact on many subsequent inventions (Ahuja and Lampert, 2001; Trajtenberg, 1990). Only a handful of inventions in a given field have a strong technological influence on future inventions and/or achieve a proficient economic impact (Achilladelis et al., 1990; Harhoff et al., 1997; Narin et al., 1987; Trajtenberg, 1990). The analysis of this rather small group of inventions is of great importance since these inventions are generally considered essential for value creation and growth of firms, as they increase competition and challenge the power of monopolists (Schumpeter and Opie, 1934). Thus, over the past decades, scholars of innovation studies have attempted to generate a stable definition and a consistent operationalisation to better understand the role of breakthrough innovation and its impact on firms and industries.

Breakthrough inventions develop new value to the market through their impact on competitive dynamics (Arts et al., 2013). Breakthroughs can be competence enhancing or competence destroying (Anderson and Tushman, 1990). In the first instance, breakthrough reinforce established firms' existing capabilities, skills, and knowledge as they serve as prior art for subsequent technological development, with a broader impact on industries and markets (Fleming, 2001). On the other hand, breakthroughs can have a competence destroying effect on established firms as they can destroy existing capabilities and core competences, although their destroying effect may be only marginal to the market (Christensen, 1997).

Previous research has generally focused on understanding the underlying mechanisms of the origin of breakthroughs. Breakthrough inventions are based on a different set of science and engineering principles than previously existing technologies (Henderson and Clark, 1990) and contain substantially dissimilar underlying technologies (Chandy and Tellis, 2006). Sometimes they might happen by the generation of new concepts that overturn old ones, but other times by architectural changes (Henderson and Clark, 1990) in which core components are combined in novel ways (Arts and Veugelers, 2014). They also can originate from the recombination of technologies from a diversity of sources (Trajtenberg et al., 1997), previously extraneous to the field of invention (Dahlin and Behrens, 2005; Shane, 2001). Thus, breakthrough inventions have been described as novel or encompassing novelty.

Many empirical indicators have been developed alongside a variety of concepts related to technological novelty. Surveys involving managers and industry experts have been used to identify novel aspects of inventions (Acs and Audretsch, 1990; Chandy and Tellis, 2006; Dutton and Dewar, 1986; Laursen and Salter, 2006). Whilst, these methods are mostly used in small studies focusing on a particular kind of invention or area, patent information is usually adopted for assessing macro-scale innovative activities. Some studies have used *ex-post* methods such as the count of citing patents (Carpenter et al., 1981; Gambardella et al., 2008; Hall et al., 2000), whilst others have employed *ex-ante* measures which rely on references to prior patents or scientific articles. The developed approaches can identify for example, the reliance on preceding knowledge (Banerjee and Cole, 2011; Gittelman and Kogut, 2003; Schoenmakers and Duysters, 2010), the breadth and scope of prior art's technological classification (Dahlin and Behrens, 2005; Fleming, 2007, 2001; Nerkar, 2003; Shane, 2001; Strumsky and Lobo, 2015; Trajtenberg et al., 1997), and shifts in cognitive knowledge (Arts and Fleming, 2018; Balsmeier et al., 2018; Gerken and Moehrle, 2012; Kaplan and Vakili, 2015).

2.1. Technological Novelty

Technology is considered as the combination of a set of components that work together in order to fulfil a human need or purpose (Arthur, 2007, 2010; Romer, 2010). These components can be assembled in various combinations and adapted to meet the needs of the task at hand. This is the essence of the *recombinant* characteristic of technology, as defined by the economics of innovation scholars such as Schumpeter and Opie (1934). Technological novelty is the introduction of unprecedented components, whereas invention novelty is a unique and novel device which may not always entail technological novelty but generally encompasses unprecedented assemblies between components (Hargadon, 1998; Nelson and Winter, 1982; Weitzman, 1998). This view dictates that no technology evolves independently of its surrounding technological environment, but at any moment throughout the technological evolution any components can be recombined with any other component (Fleming, 2001). Accordingly, the world does not advance as a disjointed aggregation of distinct trajectories but as the product of a continuous and emergent web of interactions.

The empirical literature shows that novelty generated from the re-combinatory process has the strongest contribution to higher citation rates (e.g. Arts and Veugelers, 2014; Fleming, 2001). Innovation generated from familiar technological components as well as familiar combinations generate more highly cited inventions on average, whereas the combination of novel components leads to less success on average but it increases the variability that can lead to breakthrough (Fleming, 2001; Kaplan and Vakili, 2015). Arts and Veugelers (2014), found that the novel combinations are linked to higher citations rates and increase the likelihood of breakthroughs, whereas the combinations of familiar components are generally less valuable, indicating that familiarity has a negative effect on new combinations. However, component's familiarity combined with novel combinations has the strongest impact on breakthrough inventions (Arts and Veugelers, 2014). Further studies, such as Keijl et al. (2016) demonstrated that an intermediate level of recombination – i.e., inventions created through the recombination of both familiar components as well as novel components – provides the highest impact on innovation.

Inventions embodying a combination of distinct novelty types, such as novelty in combination and components, were found to be more successful. A number of empirical studies demonstrated that inventions including new and unprecedented component as well as combinations are associated with higher citation rates and receive the highest number of citations when compared to the other novelty types (Strumsky and Lobo, 2015; Uzzi et al., 2013; Verhoeven et al., 2016). Similarly, Verhoeven et al. (2016) shows that inventions comprising several novelty indicators including novelty in recombination, novelty in scientific knowledge, and novelty in technological origins, are the most powerful source of breakthrough innovation. Interestingly, recombinant novelty is yet the most significant contributor to breakthrough inventions among several other novelty types.

2.2. Cognitive Novelty

Novelty identified through the analysis of patent's technological classes involves some drawbacks. For example, several novelty measures which are based on US technological classes work exclusively for US patents only. The USPTO classifications expose the uneven growth resulting from the first general scheme generated, in which classifications were principally designed to assist patent examiners performing searches (USPTO, 2005). As such, the classification's categories have been created under the subjective assessments of examiners based on their interpretations of the claims and the rules for making classifications (Kaplan and Vakili, 2012). Furthermore, the scope of information is limited as the description of the invention is ignored thus, technological classes may not capture the aspects of novelty attached to the scientific discoveries and cognitive ideas[9]. These issues call for the development of indicators that do not rely exclusively on technological classes but take into account textual information too.

Existing alternative approaches analyse the knowledge around the patent text and keywords. These methods involve for example, a comparison of the occurrence of keywords in patents (Li et al., 2009), the extraction and the classification of keyword (Yoon and Park, 2004), the diversity in semantic structure (Gerken and Moehrle, 2012; Yoon and Kim, 2012), the generation of novel vocabulary (Kaplan and Vakili, 2015) and the similarity of the words within the text (Arts and Fleming, 2018). Text mining approaches have also been used to analyse the novelty between patents, which have little overlap in cognitive knowledge in common with prior patents or include a combination of words or topics that appear for the first time (Balsmeier et al., 2018; Gerken and Moehrle, 2012; Kaplan and Vakili, 2015)

Gerken and Moehrle (2012) looked at the distance between a patent and its prior art semantic structure in the text using a combination of Subject-Action-Object structure and similarity indicators. They found that patents with dissimilar semantic structure from their cited patents are associated to novelty based on expert opinion. Interestingly,

[9] As Kuhn (1962) arguments that scientific ideas are embedded in vocabularies.

semantic patent analysis seems to outperform other novelty indicators based on citation (Dahlin and Behrens, 2005) and technological structure (Hall and Jaffe, 2001; Trajtenberg et al., 1997). These latter indicators perform well in the occurrence of a shift from one technological domain to another. Whilst, semantic patent analysis works well for novel patents that cite only fewer patent from other patents classes, or from the identical technological domain.

Kaplan and Vakili (2015) focused on novelty generated by the introduction of novel vocabulary (Kuhn, 1962). Their constructed indicator (i.e. *topic originating patent*) identifies those patents that are supposed to generate a new area (i.e. topic) of research. The results suggest that most of the patents considered breakthroughs in value are not cognitive novel and thus do not provide new knowledge. Instead, the generation of a new topic requires the absorption of knowledge from a narrower domain rather than combining distant and diverse technologies. Patents that cite distant and diverse prior art are more applicable to a wide range of domains and might be more likely to be cited in the future.

Knowledge originating from breakthrough innovation is known to be adopted by many following inventions (Arts and Veugelers, 2014). Although breakthroughs may not generate new subfields in a particular area of knowledge (Kaplan and Vakili, 2015), they may contribute to a particular area by providing novel knowledge to it. In line with the foundational view (Taylor and Greve, 2006; Weisberg, 1999) breakthroughs originate from a deep understanding of the foundation of a particular knowledge domain through a processes of local search. Therefore, breakthrough innovation my not necessarily introduce novel vocabulary but they may increase the usage of existing language around a specific topic. For example, the polymerase chain reaction (PCR), a revolutionary invention in biotechnology, was created from the combination of two existing technologies.

On the other hand, accoding to the tension view (Weisberg, 1999), breakthrough innovation occurs when distant technologies are introduced into new technological domains. The introduction of distant technologies would generate a shift in language from the existing vocabulary of a particular area of knowledge. This shift in language may not be due to the generation of novel words but just using existing words that have never been adopted in a particular area of knowledge. Thus, the birth of a breakthrough may lead to knowledge dissimilarity from existing prior-art.

The two indicators represent the two distinct processes of knowledge-search identified from the literature. In line with prior research (Rosenkopf and Mcgrath, 2011) suggesting that exploration and exploitation have an orthogonal relationship, as firms may be able to carry out both search processes symultaneously. Topic similarity and knowledge dissimilarity are non-significantly correlated suggesting that these two indicators are associated with two distinct dimensions of search. Furthermore, the regression analysis shows that these two variables are negatively associated with one another further suggesting two separate and often contraposing processes. Topic similarity is also negatively associated with technological recombination as well as technological radicalness, which could be interpreted as if the novelty in terms of recombination from a variety of distantly sourced components do not increase the intensity of research in a particular topic, but it has the opposite effect. In contrast radicalness and technology recombination are strongly and positively linked to increase knowledge dissimilarity from prior art citations.

3. Methodology

3.1. Data

This study adopts all patents that were granted between 1976 and 2006 by the USPTO, which data was drawn from the National Bureau of Economic Research (NBER) patent database[10] (Hall and Jaffe, 2001) and from the Patent Network Dataverse[11] (Arts and Veugelers, 2014; Li et al., 2011). The international patent classification scheme of 2006 was used to assign each patent to technological class. The dataset considered in this research comprises 3,210,361 patents filed in the USPTO between 1976 and 2001, of which patents were granted before 2004. This study looks specifically at the biotechnology industry which is an interdisciplinary field that produced many breakthrough inventions over the last few decades. The sample comprises all patents with at least one biotechnology related IPC class. In the biotech industry the vast majority of inventions are patented (Arundel and Kabla, 1998) and often single breakthrough

10 https://sites.google.com/site/patentdataproject/Home/downloads
11 https://dataverse.harvard.edu/dataverse/harvard?q=patents

inventions are assigned to only a few patents such, such as the recombinant DNA patent (US4237224), and the PCR patents (US4683202 and US4683195). Following Arts and Veugelers (2014), this paper considers the period between 1976 and 2001, as it takes the beginning of the biotechnology industry as the foundation of the Genentech firm in 1976 (Rothaermel and Deeds, 2004).

3.2. Dependent Variables

3.2.1. Breakthrough Inventions

This study analyses the relationship between textual knowledge and breakthrough innovation. A breakthrough is defined as an invention with a disproportionately large impact on future inventions and consequently the technological progress. Citations patterns can be technology specific, thus the number of high impact inventions can vary among fields (Hall and Jaffe, 2001). Following previous research, this study considers the distribution of both untruncated and truncated forward citations counts and identify outliers in the top of these distributions. For all US patents, the untruncated count of forward citations is the total number of patents citing the focal patent whereas the truncated count of forward citations is the number of citations received within five years after the year of application (Arts and Veugelers, 2014). A patent is classified as a breakthrough when both its truncated and untruncated count of forward citations are larger than the mean plus three times the standard deviation in the respective technological distribution. Furthermore, Arts et al. (2013) provide a general validity of this indicator of breakthrough in the field of biotechnology.

3.3. Independent Variables

3.3.1. Topic Similarity

Shift in language are identified by knowledge dissimilarity between a focal patent and its prior citations, whilst knowledge focus to a particular area is identified using similarity and knowledge. Topic modelling would allow the assessment of the similarity of a patent to a specific knowledge area of the biotech industry. Extending prior work, topic modelling is adopted to identify whether breakthrough inventions contribute to a particular shift in language from an area of knowledge. Thus, a novel indicator (i.e. *topic similarity*) is constructed to assess the text similarity of an invention to a particular knowledge area (i.e. topic). Furthermore, topic modelling is used to identify cognitive novel inventions (i.e. *topic originating patents*), inventions who contribute to the beginning of a new area of knowledge thus deemed novel as they introduce novel vocabulary (Kuhn, 1962; Kaplan and Vakili 2015) .

The topic modelling approach is based on the Bayesian statistical technique of Latent Dirichlet Allocation (LDA). Topic modelling allows the identification of themes among a collection of documents and to select the theme that best accounts for each document. The co-occurrence of observed words in different documents to represent a topic 'structure' (Blei, 2012). The topic modelling algorithm provides two outputs. Firstly, each word is assumed to be drawn from one of the topics, thus the beta parameter of the distribution over topics is calculated, more simply is the probability of that word being generated from that topic. Secondly, each document (i.e. in this case patents) is assigned to a list of topics weighted by their importance to the document the gamma parameter. This later step allows the quantification of the meaning over large number of texts and the identification of shift of language from knowledge areas (Chang et al., 2009). As a topic is a multinomial over a set of words a further step is needed to the labelling of topics based on words contained in them which serves as a validation for the topics produced by the model. Prior research used several methods for the automatic labelling of topics such as the best-fit model, or the hierarchical Dirichlet allocation method. However, these methods were found to be limited in terms of recognising topics with different meanings and further seem to produce a very large number of topics (Blei and Lafferty, 2007; Chen and Chang, 2010; Hall et al., 2008). Therefore, this study uses 100 topics as suggested by most of these prior studies[12].

The topic similarity indicator is constructed as follows. The text information included in the title and the abstract of each patent is used following Arts et al., (2018) methodology[13]. The USPTO requires the abstract to be up to a maximum of 150 words allowing to compare patents with text of equal lengths, to which the information present in the title's text is further included. Stop words are removed as they do not contribute to the identification of topics, and 100 separate topics are identified including the probability

12 The process of topics validation by experts was not performed; however, this was manually carried out by the author. The author considers this as a current limitation of the proposed methodology and seeks to expand on this further in later developments.

13 https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/JO2DQZ

of each word occurring in each topic and the weight of each topic in each abstract. This approach then assigns for each patent the topic with the highest gamma value. Those patents with a gamma value higher than the topic average gamma are assigned to one and deemed *topic similar* patents, or zero otherwise.

Table 17 reports the values for precision and recall used for pattern recognition, which indicate the fraction of relevant breakthroughs among the retrieved elements, and the fraction of the relevant breakthroughs that over the total amount of relevant elements. This approach identifies a substantial number of topic similar patents, around 27% of the whole biotechnology sample, which drastically reduces the precision of recognising only breakthroughs. Around 41% of all three standard deviation breakthroughs are identified as having above average topic vocabulary, thus increasing the knowledge around a given topic. To increase the precision and recall of this approach only patents appearing between 5 and 20 years after the topic formation are considered, as most of breakthroughs occur up to twenty years from the beginning of a topic (see Figure 4, Appendix.2). However, around 26.8% are identified as type 1 errors (false positive) and 59% of the sample as type 2 errors (false negatives). This result suggest that the largest part of breakthroughs has a lower than average gamma. Therefore, a further indicator is constructed (i.e. *topic dissimilar*), which would identify patents with a gamma value below the topic average. The precision and recall for *topic dissimilar* patents are reported in Table 24 Appendix 3.

Table 17: Precision and recall for Topic Similar patents

N.	Variance	150 Topics	100 Topics	50 Topics	20 Topics
1	Precision	1.01	1.04	1.07	1.15
2	Recall	44.94	43.71	43.26	49.89
3	Type 1 error	26.57	25.14	24.30	26.01
4	Type 2 error	55.06	56.29	56.74	50.11

Notes: Based on a sample of 146,768 biotechnology patents

Figure 5 shows two examples of the newly construct *topic similarity* patents with an above average frequency of topic words in that topic: in other words, patents with high intensity vocabulary of a specific topic are represented. Those patents with a topic gamma higher than the yearly average topic gamma are identified as *topic similarity patents.* The figure shows both the average for breakthrough patents from the biotech sector located in the topic with a continuous line, and the average of incremental patents. It is clear that this approach identifies some incremental patents (those one with an above average gamma) as topic similar patents, whereas those breakthroughs that have a below average topic similarity are identified as outliers. Topic 2 (left graph) comprises the (in)famous breakthrough discovery of the recombinant DNA by Cohen and Boyer (US4237224) applied in 1979, whilst topic 52 (right graph) comprises the PCR patents (US4683202 and US4683195) applied in 1985 and 1986 respectively. The figure shows the topic originating patents for the two topics. Interestingly, topic 52 topic originating patent (US4302204) is considered a breakthrough, whereas for topic 2 the topic originating patent (US4190495) although highly cited is not considered a breakthrough.

Topics in the biotechnology sector are identified based on the assumption on the number of subfields that have been created in the biotechnology sector, and the number of breakthrough inventions that topics are able to identify. This last point is assessed using pattern recognition (i.e. precision and recall). Precision identifies the fraction of relevant breakthrough among the retrieved elements, whilst recall identifies the fraction of relevant breakthroughs over the total amount of relevant elemetns. An iterative process was carried out starting from 20 and increasing to 150 topics. Twenty topics gives the best estimates for breakthrough identification, highest precision and recall, and lowest number of type II errors. However, 20 topics does not seem to be representive of the whole biotechnology sector, as a larger number of subfields are supposed to have grown over the period studied. Prior research suggests up to 100 subfields. By visual inspections there is no overlapping in words between 100 topics. Furthermore, 100 topics gives higher recall and a lower type II errors than 50 topics. Lastly, 150 topics gives marginally more efficient type II and recall parameters but it is substantially more time consuming than 100 topics. Thus, 100 topics is a good trade off between computing time and patttern recognition efficiency.

Figure 5 further shows those patents that include the entry of a particular topic within a threshold weighting for that topic (i.e. gamma) of 0.2 and having the same application year of the topic formation, which are identified as *topic originating patents* (Kaplan and Vakili, 2015). This is a binary measure that identify patents above the threshold as 1 and those outside 0. This approach classifies 28 topics with only 1 topic originating patent, 40 topics with a maximum of 10, and 32 with above 10 topic originating patents.

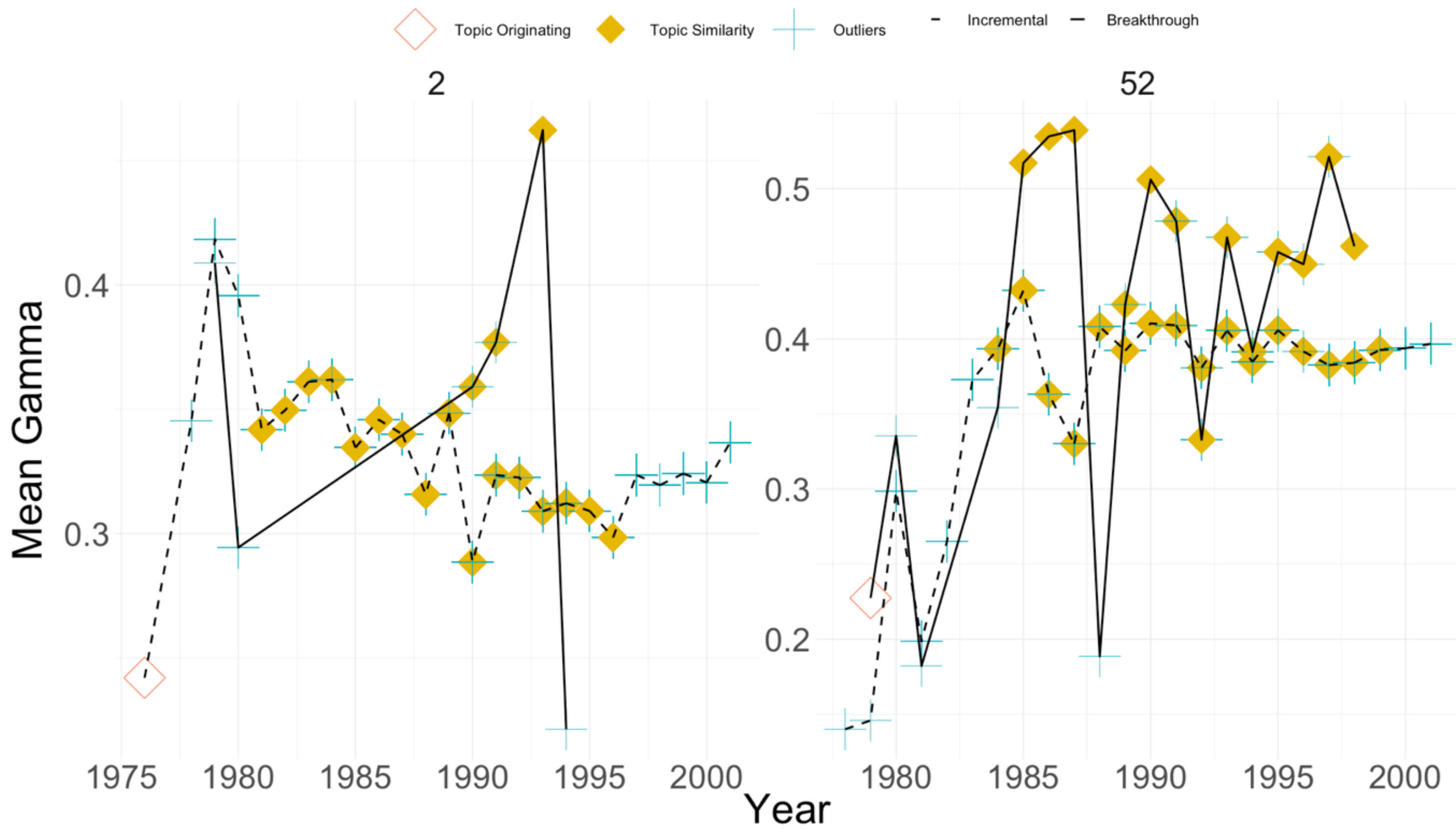

Figure 5: Identification of patent with a vocabulary intensity above the topic yearly average

3.3.2. Knowledge Dissimilarity

For the identification of those patents that use different knowledge from their prior art citations the text matching technique called Jaccard Index is adopted following a series of prior studies (Arts et al., 2018; Gerken and Moehrle, 2012; Moehrle, 2010). This technique would allow to capture the shift in knowledge between a focal patent and its prior art citations. The Jaccard similarity index is calculated by dividing the number of unique keywords in the title and the abstract of focal patent by the number of unique keywords in the union of the title and the abstract the focal patent and each individual backward citation. The Dissimilarity of a patent is then taken as one minus the highest Jaccard index similarity among the backward citations. Thus, Knowledge dissimilarity is an indicator variable where 1 identifies the highest level of dissimilarity whilst 0 the lowest.

$$Knowldge\ Dissimilarity_i = 1 - \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \qquad \text{(eq.1)}$$

3.4. Control Variables

This study controls for different characteristics of technological novelty. Following Arts and Veugelers (2014), this study uses a measure of *novel combinations* which identify the number of first-time combinations in the whole USPTO database, between technological components of each invention. As each patent can have multiple technological components this measure is the average number of novel combinations among the whole component's spectrum of each patent (eq.2). Thus, a novel combination is a measure of a patent's number of unprecedented subclass pairs divided by the patent's total number of subclass pairs, resulting in a number between 0 and 1. To measure the familiarity of components this study uses the *component familiarity* measure developed and adopted in previous studies (Arts and Veugelers, 2014; Fleming, 2001; Kaplan and Vakili, 2015). This measure captures the individual component subclass familiarity when a component has been used in previous inventions prior to the focal patent. Each individual component familiarity is then summed to a total and its average calculated. Furthermore, in line with previous research this analysis considers the 18% yearly knowledge loss ratio for the average familiarity measure. The procedure used by Arts and Veugelers (2014) for the construction of these variables was followed carefully. An example of how these variables are constructed is reported in Table 2 and Table 23 in the appendix.

$$Recombinant\ Novelty_i = \frac{First\ time\ Technological\ Class\ Combination_i}{Total\ Number\ of\ Technological\ Classes\ _i} \qquad \text{(eq.2)}$$

$$Components\ Familiarity_i = \sum_{k}^{n} 1\{patent\ k\ uses\ citation\ j]xe^{-\left(\frac{application\ year\ i - application\ year\ k}{time\ costant\ of\ knowledge\ loss}\right)} \qquad \text{(eq.3)}$$

Shane (2001) and Briggs and Buehler (2018) adopted a measure of novelty which mixes the two aspects of novelty: novelty by origin and novelty by technological characteristics. *Radicalness* combines the novelty aspect in diversity of technological components of the focal invention and the novelty aspect of the diversity in prior-art citations. Radicalness is measured by counting all unique three-digit patent classes in which the focal patent's prior art citations build upon, but the focal patent itself is not classified. Patent citations to patents in particular technical fields represent the USPTO's assessment that particular invention builds upon knowledge in that technical field. Anytime a patent cites prior patents in classes distinct from the ones it is classified, this can be a signal that the invention builds upon different technical paradigms from the one in which it is applied (Shane, 2001).

This study further controls for inventions level characteristics which could have an impact on the innovation performance. Following prior research (Arts and Veugelers, 2014; Fleming, 2001), this study controls for a few invention-level characteristics including *backward citations*, as the number of citations to prior-art inventions, *number of classes* and *number of subclasses* as the number of 1-digit and 4-digit classes and subclasses respectively of the focal patent, and the number of *new subclass* every first-time occurrence of a subclass which is introduced in a patent. Moreover, *newest subclass* controls for the number of previous uses among the focal patent's subclasses, as the success of an invention could have produced the introduction of a new subclass through the ex post reclassification process. Furthermore, additional analysis is carried out including variables related inventors characteristics such as, *team size* as the number of assignees of the focal patent, *experience diversity* as the number of technological classes at least one of the focal patent assignees has patented in before, *average experience* as the average number of prior patents by the focal patent inventors.

3.5. Empirical Analysis

This study aims to analyse the relationship between different cognitive novel patent indicators as well as studying the relationship between cognitive knowledge and breakthrough innovation. Therefore, probit models are adopted for estimation of the likelihood of a patent being a breakthrough whereas logit models are used for the relationship between cognitive knowledge indicators with a continuous value between zero and one. Furthermore, the maximum likelihood estimator is adopted for consistent, efficient and asymptotically normal estimates.

4. Results

4.1. Summary Statistics

Table 18 reports the summary statistics of both dependent and independent variables for the sample of biotechnology patents. Most of the explanatory variables are in logarithmic form and 1 was added to those variables with minimum value equal zero.

Table 19 shows the averages for the sample of non- and breakthrough patents in Column 1 and 2 respectively, plus an illustrative example of six breakthrough patents (Column 3 to 8) from the whole sample. The sample includes the (in)famous breakthrough discovery of the recombinant DNA in 1973 by Cohen and Boyer (US4237224) (Column 3) the PCR patents (US4683202 and US4683195) (Column 5 and 6). Furthermore, three more patents are discussed, these are among the hundred most influential biotech patents ever produced (Appio, 2013; Arts et al., 2013). These include a patent which is not coded as a breakthrough, the method for cloning genes (US4394443) (Column4), and two other breakthrough patents with among the highest number of backward citations, the process for amplifying, detecting, and/or cloning nucleic acid sequences using a thermostable enzyme (US4965188) (Column 7) and the large scale photolithographic solid phase synthesis of polypeptides and receptor binding screening thereof (US5143854) (Column 8).

Table 18: Descriptive statistics (146,768 patents)

N.	Variable	Description	Mean	St.dev	Min	Max
1	Topic Similarity	Patent with an above the average intensity of vocabulary of a specific topic	0.25	0.44	0	1
2	Topic Originating Patent	Patent that contribute to the beginning of a new area of knowledge	0.01	0.10	0	1
3	Single subclass	Binary: single technology subclass	0.06	0.24	0	1
4	Radicalness	The degree to which an invention sources in knowledge from outside its own field	0.92	0.83	0	4.88
5	Patent References	The number of backward patent citations	1.28	0.97	0	5.91
6	Number of subclasses	The number of technology subclasses	1.73	0.68	0	5.12
7	Number of classes	The number of technology classes	1.07	0.37	0	2.83
8	Non patent references	The number of citations to non-patent literature	1.99	1.42	0	6.98
9	Newest Subclass	The minimum number of previous uses among the focal patent's subclasses	4.11	1.62	0	9.52
10	New Subclass	Binary: at least one subclass appears for the first time in history	0.01	0.07	0	1
11	Knowledge Dissimilarity	Difference in knowledge between a focal patent and its prior citations	0.88	0.22	0	1
12	Forward Citations7606	Number of forward citations received	5.89	14.30	0	1,555
13	Forward Citations	Number of forward citations received within 5 years	2.41	5.12	0	201
14	Failures	Patent received no forward citations within 5 years	0.23	0.42	0	1
15	Component Familiarity	Recent and frequent usage of the focal patent's subclasses by all prior US patents	5.27	1.70	0	9.31
16	Combination Novelty	The focal patent's number of pair-wise subclass combinations which appear for the first time in history divided by the total number of pair-wise subclass combinations	0.17	0.25	0	1
17	Breakthrough	Binary: 3 standard deviation outliers in distribution of forward citations	0.01	0.08	0	1

Notes: All explanatory count variables are logged after adding one for those variables with zero values

Table 19: Example of Six Biotechnology Breakthroughs

	1	2	3	4	5	6	7	8
Patent Number			4237224	4394443	4683202	4683195	4965188	5143854
Application Year			1979	1980	1985	1986	1987	1990
Breakthrough	0	1	1	0	1	1	1	1
Forward Citations	2.17	41.09	94.00	13.00	76.00	101.00	32.00	119.00
Forward Citations7606	5.35	94.51	256.00	224.00	1555.00	1460.00	586.00	729.00
Failures	0.23	0.05	0.00	0.00	0.00	0.00	0.00	0.00
Topic Similarity	0.25	0.44	0.00	0.00	1.00	1.00	1.00	0.00
Knowledge Dissimilarity	0.88	0.88	1.00	1.00	1.00	0.96	0.51	0.92
Topic Originating Patent	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Combination Novelty	0.17	0.22	0.96	0.73	0.50	0.52	0.17	0.47
Component Familiarity	5.27	5.17	2.27	3.67	4.05	4.25	5.26	5.05
New Subclass	0.01	0.03	1.00	1.00	1.00	0.00	0.00	0.00
Newest Subclass	4.11	3.62	0.00	0.00	0.00	0.69	1.39	3.64
Non patent references	1.99	2.67	3.18	3.22	1.79	2.89	2.64	4.82
Number of classes	1.07	1.23	1.39	1.39	1.10	1.10	0.69	1.39
Number of subclasses	1.73	2.03	3.22	1.95	1.79	2.08	1.61	2.77
Patent References	1.28	1.92	0.00	0.00	0.00	0.69	1.95	3.50
Radicalness	0.92	1.52	0.00	0.00	0.00	0.69	1.10	3.50
Single subclass	0.06	0.04	0.00	0.00	0.00	0.00	0.00	0.00

Table 19 shows that breakthrough inventions have on average higher topic similarity than non-breakthrough inventions. Interestingly, both breakthrough and incremental inventions have the same amount of knowledge dissimilarity to their prior art citations. Breakthroughs show higher average combination novelty and lower component familiarity. They also have higher average radicalness, number of classes and number of subclasses. Furthermore, they have nearly double the average number of scientific references, and a large number of backward patent citations.

Table 25 (see Appendix.2) displays the correlations among the distinct variables. The independent variable of interest Topic similarity and Knowledge similarity are only slightly correlated to other independent variables considering technological characteristics. This indicates that text-based indicators denote a distinct characteristic of innovation, which is of a cognitive kind and thus related to the vocabulary of patents which might not be captured by technological classes.

4.2. Relationship between Knowledge and Topic Similarity

Table 20 shows that the two patent text variables topic similarity and knowledge dissimilarity are negatively associated with each other, indicating that patents with an intense vocabulary of a specific topic tend to use words that have been previously used by prior art. In contrast, topic dissimilarity which represent patents with an intensity of vocabulary lower than the topic average, is positively correlated with knowledge dissimilarity from prior art citations. Interestingly, topic similarity is also negatively associated with technological recombination as well as technological radicalness, which could be interpreted as if the novelty in terms of recombination from a variety of distantly sourced components do not increase the intensity of research in a particular topic, but it has the opposite effect. In contrast radicalness and technology recombination are strongly and positively linked to knowledge dissimilarity from prior art citations. Furthermore, having more citation to prior art increases the likelihood of topic similarity. Lastly, Table 19 reports the relationship between topic originating patents and other measures of cognitive and technological novelty to stimulate a comparison of the results to prior research. In line with Kaplan and Vakili (2015), topic originating patents are negatively associated with recombinant novelty. Topic originating patents are further negatively correlated with knowledge dissimilarity, although this may be partially due to the low number of patent citations demonstrated by the strong negative link between the patent reference control variable. This may also justify the insignificant estimator of radicalness, as this would be expected to be negatively associated with the beginning of cognitive knowledge following prior studies' findings.

Table 20: Probit and Logit Models on Knowledge Dissimilarity and Topic Similarity

	Topic Similarity	Knowledge Dissimilarity	Topic Originating Patent
	Probit (1)	Tobit (2)	Probit (3)
Knowledge Dissimilarity	-0.149***		-0.727***
	(0.021)		(0.197)
Topic Similarity		-0.009***	
		(0.002)	
Combination Novelty	-0.166***	0.042***	-0.377**
	(0.020)	(0.004)	(0.121)
Component Familiarity	-0.002	-0.008***	-0.073
	(0.006)	(0.001)	(0.049)
Radicalness	-0.049***	0.021***	-0.024
	(0.009)	(0.002)	(0.102)
Patent References	-0.012	-0.174***	-0.214**
	(0.008)	(0.002)	(0.104)
Non patent references	-0.001	0.009***	-0.004
	(0.003)	(0.001)	(0.048)
Number of classes	0.020	0.041***	-0.070
	(0.018)	(0.003)	(0.159)
Number of subclasses	0.004	-0.012***	-0.004
	(0.010)	(0.002)	(0.093)
Single subclass	-0.053**	0.010**	-0.200
	(0.020)	(0.004)	(0.133)
Newest Subclass	0.004	0.000	-0.237***
	(0.006)	(0.001)	(0.053)
Constant	-1.379***	1.264***	2.901***
	(0.045)	(0.051)	(0.319)
Year Fixed Effects	Yes	Yes	Yes
Technology Fixed Effects	Yes	Yes	Yes
Observations	109662	119470	57567
Log lik.	-56236.6	-27625.9	-542.3
Chi-squared	18216.8		4505.6

The table gives parameter estimates including robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The findings on the relationship between knowledge dissimilarity and topic similarity suggest that increasing the knowledge around a topic requires brand new words that should not necessarily be dissimilar from prior art citations and use more radical and recombinant technologies. On the other hand, patents that are deemed topic dissimilar have dissimilar words to their prior art and tend to be linked to more diverse (i.e. radical) technologies and recombinant novelty (Table 19). As breakthrough have been found to be highly associated with technological recombination and radical technology (Arts and Veugelers, 2014; Briggs and Buehler, 2018; Kaplan and Vakili, 2015; Shane, 2001) the results would suggest that those patents that shift their vocabulary away from the average of their knowledge area have an increased likelihood of encompassing technological novelty and further being breakthroughs. The next section aims to demonstrate the link between which type of cognitive knowledge increases the likelihood of breakthrough innovation.

Topic similarity is associated with the narrow search into a particular topic. Topic similarity indicates whether a breakthrough makes intensive use of a specific vocabulary (i.e. topic – a group of keywords defining an area of knowledge). This indicator is negatively associated with combination novelty and radicalness further indicating its link to narrow search. Whereas knowledge dissimilarity indicates a shift in language from prior-art knowledge. A shift can occur either when novel vocabulary is created, or existing vocabulary is introduced into another domain. This is positively associated with combination novelty as well as radicalness suggesting that inventions that build from different cognitive knowledge draw vocabulary from other domains, further indicating association with broad search. Lastly, topic similarity and knowledge dissimilarity are non-significantly correlated suggesting that these two indicators are associated with two distinct dimensions of search.

4.3. Cognitive Knowledge and Breakthrough Innovation

Table 21 reports the results from the probit regression on breakthrough inventions. In line with prior assumptions, knowledge dissimilarity is strongly positively associated with breakthrough indicating that highly cited patents involve a shift in knowledge from prior art citations. Interestingly, topic similarity is positively associated with breakthrough innovation whereas topic dissimilarity decreases the likelihood of breakthrough. This is informative regarding the knowledge produced by breakthrough inventions, which suggests that most of breakthroughs increase the knowledge around a particular area. This further suggest that breakthroughs have dissimilar knowledge to their prior art citations because they generate new words that contribute to the development of a particular field more than simply using words from different contexts that would appear new to the field.

Table 21: Probit Models on Breakthrough Inventions

	3stdev	3stdev	3stdev	3stdev	2stdev	4stdev	3stdev	3stdev	3stdev
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Knowledge Dissimilarity		0.228**		0.371**	0.407**	0.364**	0.376**	0.329**	0.338**
		(0.068)		(0.099)	(0.074)	(0.129)	(0.099)	(0.099)	(0.099)
Topic Similarity			0.073**	0.325**	0.288**	0.535**	0.325**	0.332**	0.331**
			(0.028)	(0.122)	(0.094)	(0.146)	(0.122)	(0.121)	(0.121)
Knowledge Dissimilarity x Topic Similarity				-0.281*	-0.253*	-0.505**	-0.283*	-0.279*	-0.281*
				(0.134)	(0.104)	(0.162)	(0.135)	(0.134)	(0.134)
Combination Novelty							0.421+		0.437*
							(0.217)		(0.218)
Component Familiarity							0.024		0.028
							(0.019)		(0.019)
Combination Novelty x Component Familiarity							-0.094*		-0.110*
							(0.047)		(0.048)
Radicalness								0.194**	0.200**
								(0.026)	(0.026)
Patent References	0.249**	0.260**	0.249**	0.260**	0.246**	0.247**	0.264**	0.120**	0.120**
	(0.014)	(0.015)	(0.014)	(0.015)	(0.011)	(0.018)	(0.015)	(0.024)	(0.024)
Non Patent References	0.085**	0.086**	0.086**	0.088**	0.094**	0.086**	0.085**	0.089**	0.085**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.012)	(0.010)	(0.010)	(0.010)
Number of Classes	0.266**	0.263**	0.265**	0.262**	0.292**	0.340**	0.266**	0.273**	0.286**
	(0.050)	(0.050)	(0.050)	(0.050)	(0.037)	(0.063)	(0.051)	(0.050)	(0.051)
Number of Subclasses	0.080**	0.081**	0.080**	0.082**	0.092**	-0.005	0.079**	0.083**	0.078**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.021)	(0.036)	(0.029)	(0.028)	(0.029)
Single Subclass	0.215**	0.213**	0.215**	0.213**	0.219**	0.216*	0.237**	0.199**	0.222**
	(0.071)	(0.071)	(0.071)	(0.071)	(0.052)	(0.087)	(0.073)	(0.071)	(0.073)
Newest Subclass	-0.083**	-0.082**	-0.083**	-0.082**	-0.074**	-0.107**	-0.091**	-0.080**	-0.095**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.009)	(0.015)	(0.015)	(0.012)	(0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146.768	146.768	146.768	146.768	146.768	146.768	146.768	146.768	146.768
Log Likelihood	-4.654.059	-4.647.984	-4.650.575	-4.641.892	-8.642.738	-2.818.223	-4.639.677	-4.613.044	-4.609.636

Note: The table gives parameter estimates including robust standard errors in parentheses.

+ p<0.1; * p<0.05; ** p<0.01

The interaction between knowledge dissimilarity and topic similarity is negative suggesting that when the dichotomous variable (i.e. in this case topic similarity) is unity knowledge dissimilarity increases whereas when this is zero the knowledge dissimilarity loses its strength. This indicates that those breakthroughs that increase the vocabulary of a given topic have a distinct text from their prior-art citations. Patents having different text from prior art-art citations could be due to either the introduction of novel words, as well as not having any patent citations (e.g. Patent N.: 4683202). However, the results remain unchanged after introducing a dummy to control for patents with no patent references (Model 21 – Table 26 in Appendix.5), which supports the first hypothesis.

The results presented in Table 21 include the two- and four- standard deviation outliers to either increase or decrease the level of rigour of the breakthrough variable. As demonstrated in the columns 5 and 6 of the table, the results remain consistent across these distinct breakthrough classifications. Furthermore, topic similarity impact on breakthrough increases the more restrictive is the construction of the breakthrough sample (i.e. using 4-standard deviation). This indicates that the greater the technological impact, the more novel words are introduced and the greater the increase in knowledge around a specific topic. In contrast, knowledge diversity is slightly reduced when considering breakthrough at four standard deviation, and its interaction with cognitive novelty increases significantly reducing its impact. This may indicate that the larger the impact of breakthroughs the smaller their dissimilarity from prior-art. This could be due to either breakthrough not citing any prior patent or only comprising incremental knowledge from their cited patents.

5. Discussion

The two developed indicators detect shifts in knowledge by looking at whether a patent vocabulary differs from either its prior-art citations or the average of a given knowledge area. The latter indicator can in turn identify inventions that either increment or disrupt the knowledge around specific area, by looking at whether they have respectively above or below the average topic vocabulary. The findings show that inventions with a lower than average topic vocabulary are associated with recombinant novelty, broad and distant technologies, and further have a dissimilar text from their prior art citations. In contrast, inventions that increase the language above the average of a particular knowledge area are negatively correlated to all the above aspects of novelty.

The findings indicate that in general the vocabulary of breakthrough inventions tends to be substantially different from prior art citations, which suggest that novel discoveries may increment the occurrence of novel words. Surprisingly, breakthrough inventions are positively associated with shift in language that increase the knowledge around particular areas. The analysis revealed that the breakthroughs that do so have a higher knowledge dissimilarity to their prior-art citations, which reinforce the idea that they introduce novel vocabulary. It is possible that novel vocabulary is linked to scientific discoveries (e.g. Pat. N.: 4683195 and 4683202), However, in Table 21 the non-patent reference estimator is negatively associated with topic similarity not supporting this idea.

The second group of breakthroughs have a more disruptive character as their shift in language does not contribute to particular knowledge areas. They generate from the recombination of technologies from broad and distant domains. The analysis shows that this group is negatively correlated to the patent citations, whilst being positively linked to scientific research. Furthermore, they have low knowledge dissimilarity from their prior art citations suggesting that they vocabulary is incremental and do not represent any introduction of novel vocabulary.

This study is nonetheless subject to a number of limitations, concerning the reliability of text-mining techniques, the restrictive use of patent data, and the scope of the research. As previously highlighted in the literature, text-mining techniques have some limitations (Arts et al., 2018; Moehrle, 2010). For example, false negative often correspond to patents with different yet closely related keywords as well as keywords with different spellings and synonyms. Type one errors or false positives often matches the same tools and the methods that are used for different applications in difference contexts. More general keywords such as method, system, device, apparatus which have many different applications across different fields. Regarding topic modelling, this technique is based in the generation of posterior probabilities which means that the identification of topics is subject to which patents are included in the analysis. Also, the technique is affected by which patents are granted, and which type of patents the author decides to use in the analysis. Finally, as not all inventions are patented, patents are a biased source of innovation (Griliches, 1990; Harhoff et al., 1997). Nevertheless, patent content allows the identification of a substantial share of the innovation process in particular in scientific areas as in the biotechnology industry.

6. Conclusion

Most of prior studies focusing on breakthrough have dealt with the technological characteristics of novelty. Yet, a much-neglected aspect of novelty relates to the development of new ideas in the form of novel vocabulary or shift in the existent one (Kaplan and Vakili, 2015, 2012). As such, this paper focus on taking a step forward in understanding the textual characteristics of breakthrough inventions. It develops two indicators to measure the textual similarity between a focal patent and a its prior-art citations, as well as to a given knowledge area. This other approach adopts topic modelling for the creation of topics of knowledge by using information of patents from 30 years of the biotech industry.

The findings contribute to the field of novelty and breakthrough innovations (e.g. Ahuja and Lampert, 2001; Arts and Veugelers, 2014; Kaplan and Vakili, 2015) as it shows that breakthroughs are linked to shifts in knowledge from both prior-art citations and specific area of knowledge. The findings lead to an advancement of the approach of text-mining techniques for the identification of cognitive knowledge between patents (Arts and Fleming, 2018; Balsmeier et al., 2018; Gerken and Moehrle, 2012; Kaplan and Vakili, 2015). The use of text mining techniques for the identification of knowledge similarity characteristics may be useful for managers and practitioners looking at technology monitoring for the understanding of technological change, and for innovation or scientists for the assessment of the quality of innovations.

Appendices

Appendix.1 Combination Novelty & Component Familiarity

Table 22: Example of Combination Novelty of the PCR patent (US4583195)

	Subclass pair		First time
1	435/6	435/91.2	1
2	435/6	435/91.41	0
3	435/6	436/501	0
4	435/6	436/508	0
5	435/6	436/63	0
6	435/6	436/94	0
7	435/91.2	435/91.41	1
8	435/91.2	436/501	1
9	435/91.2	436/508	1
10	435/91.2	436/63	1
11	435/91.2	436/94	1
12	435/91.41	436/501	0
13	435/91.41	436/508	1
14	435/91.41	436/63	1
15	435/91.41	436/94	1
16	436/501	436/508	0
17	436/501	436/63	0
18	436/501	436/94	0
19	436/508	436/63	1
20	436/508	436/94	1
21	436/63	436/94	0

Table 23: Example of Component Familiarity of the PCR patent (US4583195)

	Subclass	# Prior Patents	# Prior patents corrected for knowledge loss
1	435/6	181	144.8
2	435/91.2	1	0.8
3	435/91.41	77	61.6
4	436/63	141	112.8
5	436/94	50	40
6	436/501	122	97.6
7	436/508	34	27.2

Appendix.2 Distribution of Breakthrough Innovation Across Topics

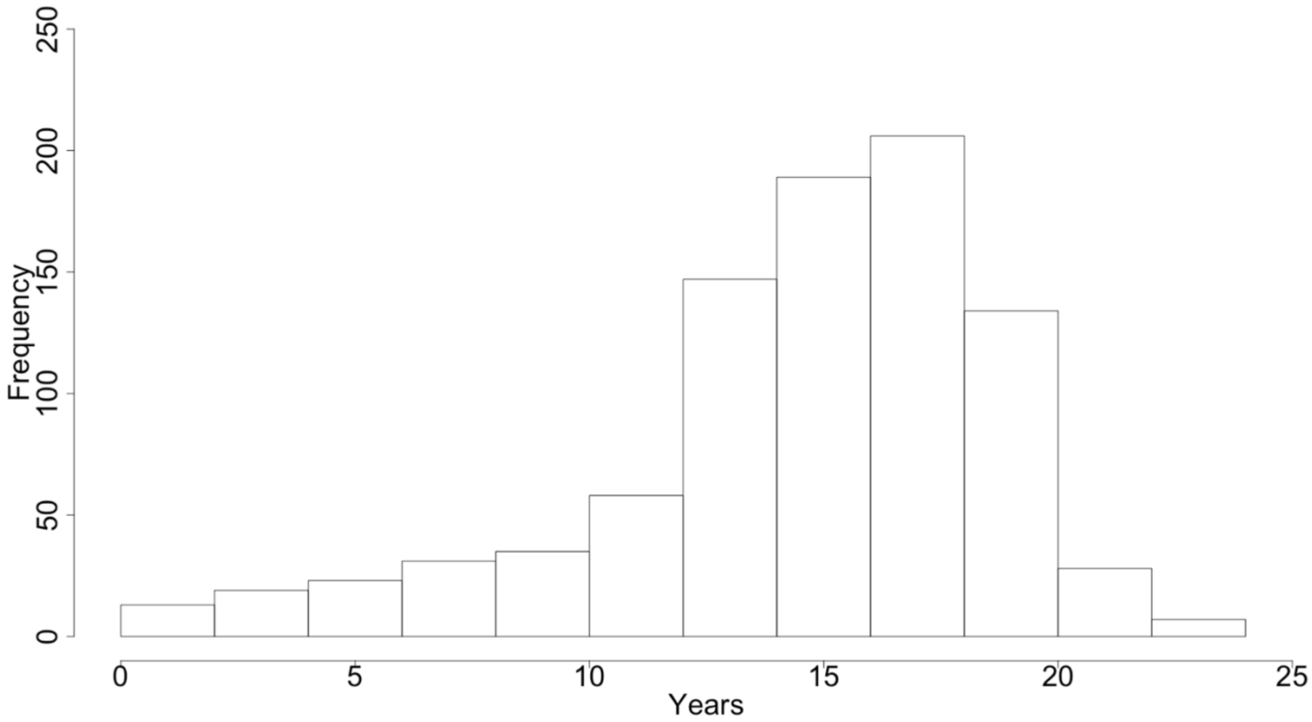

Figure 6: Distribution of Breakthrough Inventions within Topics

Appendix.3 Relevance Measures

Table 24: Precision and Recall for Topic Dissimilar Patents

N.	Relevance	150 Topics	100 Topics	50 Topics	20 Topics
1	Precision	0.84	0.89	0.95	0.82
2	Recall	47.42	48.76	48.43	41.91
3	Type 1 error	34.11	32.99	30.53	30.82
4	Type 2 error	52.58	51.24	51.57	58.09

Notes: Based on a sample of 146,768 biotechnology patents

Appendix.4 Correlation Matrix

Table 25: Pearson Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Breakthrough																
Forward Citations	0.59*															
Forward Citations7606	0.48*	0.65*														
Failures	-0.03*	-0.13*	-0.05*													
Topic Similarity	0.03*	0.08*	0.10*	0.00												
Knowledge Dissimilarity	0.00	0.00	0.03*	0.02*	0.01*											
Topic Originating Patent	-0.01	-0.01*	0.01*	0.02*	-0.06*	0.03*										
Combination Novelty	0.02*	0.04*	0.12*	0.06*	0.01*	0.09*	0.10*									
Component Familiarity	0.00	0.02*	-0.09*	-0.01*	-0.03*	-0.07*	-0.15*	-0.30*								
Radicalness	0.06*	0.14*	0.08*	-0.01*	-0.03*	-0.20*	-0.09*	0.00	0.04*							
Patent References	0.05*	0.14*	0.07*	-0.02*	-0.02*	-0.30*	-0.11*	-0.04*	0.07*	0.81*						
Non patent references	0.04*	0.08*	0.02*	-0.04*	-0.02*	-0.11*	-0.10*	-0.14*	0.21*	0.19*	0.23*					
Number of classes	0.03*	0.11*	0.10*	0.01*	0.06*	0.01	0.00	0.18*	0.39*	-0.01*	0.03*	-0.04*				
Number of subclasses	0.03*	0.11*	0.10*	0.01*	0.05*	-0.03*	-0.02*	0.15*	0.39*	0.04*	0.08*	0.01*	0.71*			
Single subclass	-0.01*	-0.03*	-0.02*	0.03*	-0.01*	0.03*	0.03*	-0.17*	-0.09*	-0.03*	-0.06*	-0.05*	-0.26*	-0.38*		
Newest Subclass	-0.02*	-0.01*	-0.14*	-0.02*	-0.04*	-0.06*	-0.13*	-0.42*	0.80*	0.04*	0.04*	0.11*	0.13*	0.04*	0.12*	
New Subclass	0.03*	0.03*	0.09*	0.01*	0.00	0.02*	0.06*	0.14*	-0.08*	-0.03*	-0.03*	-0.01*	0.03*	0.03*	-0.01*	-0.18*

Note: *p<0.01

Appendix.5 Regression Analysis on Breakthrough Innovation

Table 26: Probit Model on Breakthrough Innovation

	3stdev	3stdev	3stdev	3stdev	2stdev	4stdev	3stdev	3stdev	3stdev	3stdev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Knowledge Dissimilarity		0.228**		0.371**	0.407**	0.364**	0.376**	0.329**	0.338**	0.353**
		(0.068)		(0.099)	(0.074)	(0.129)	(0.099)	(0.099)	(0.099)	(0.098)
Topic Similarity			0.073**	0.325**	0.288**	0.535**	0.325**	0.332**	0.331**	0.319**
			(0.028)	(0.122)	(0.094)	(0.146)	(0.122)	(0.121)	(0.121)	(0.121)
Knowledge Dissimilarity x Topic Similarity				-0.281*	-0.253*	-0.505**	-0.283*	-0.279*	-0.281*	-0.276*
				(0.134)	(0.104)	(0.162)	(0.135)	(0.134)	(0.134)	(0.133)
Combination Novelty							0.421+		0.437*	
							(0.217)		(0.218)	
Component Familiarity							0.024		0.028	
							(0.019)		(0.019)	
Combination Novelty x Component Familiarity							-0.094*		-0.110*	
							(0.047)		(0.048)	
Radicalness								0.194**	0.200**	
								(0.026)	(0.026)	
Patent References	0.249**	0.260**	0.249**	0.260**	0.246**	0.247**	0.264**	0.120**	0.120**	0.293**
	(0.014)	(0.015)	(0.014)	(0.015)	(0.011)	(0.018)	(0.015)	(0.024)	(0.024)	(0.017)
Non-Patent References	0.085**	0.086**	0.086**	0.088**	0.094**	0.086**	0.085**	0.089**	0.085**	0.084**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Number of Classes	0.266**	0.263**	0.265**	0.262**	0.292**	0.340**	0.266**	0.273**	0.286**	0.261**
	(0.050)	(0.050)	(0.050)	(0.050)	(0.037)	(0.063)	(0.051)	(0.050)	(0.051)	(0.050)
Number of Subclasses	0.080**	0.081**	0.080**	0.082**	0.092**	-0.005	0.079**	0.083**	0.078**	0.081**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.021)	(0.036)	(0.029)	(0.028)	(0.029)	(0.028)
Single Subclass	0.215**	0.213**	0.215**	0.213**	0.219**	0.216*	0.237**	0.199**	0.222**	0.205**
	(0.071)	(0.071)	(0.071)	(0.071)	(0.052)	(0.087)	(0.073)	(0.071)	(0.073)	(0.071)
Newest Subclass	-0.083**	-0.082**	-0.083**	-0.082**	-0.074**	-0.107**	-0.091**	-0.080**	-0.095**	-0.082**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.009)	(0.015)	(0.015)	(0.012)	(0.015)	(0.012)
No Patent Reference										0.180**
										(0.053)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146.768	146.768	146.768	146.768	146.768	146.768	146.768	146.768	146.768	146.768
Log Likelihood	-4.654.059	-4.647.984	-4.650.575	-4.641.892	-8.642.738	-2.818.223	-4.639.677	-4.613.044	-4.609.636	-4.636.259

Note: The table gives parameter estimates including robust standard errors in parentheses.
+ p<0.1; * p<0.05; ** p<0.01

Chapter V

GENERAL CONCLUSION

"The tendency to variation is a chief cause of progress; and the abler are the undertakers in any trade the greater will this tendency be."

- *(Marshall, 1890:295)*

Prior research has shown that technology and inventions develop from strategic processes of learning and searching for sources of novelty (Katila and Ahuja, 2002; March, 1991). Novelty is essential for the generation of breakthrough innovation but at the same time it implies risks and uncertainty (Ahuja and Lampert, 2001; Arts and Veugelers, 2014). Thus, novelty has been portrayed as both a saviour and a villain in the literature (Rosenkopf and Mcgrath, 2011). Empirical evidence suggests that firms should carefully plan and design their learning processes of searching for acquiring new knowledge, and moderately adopt distantly sourced technologies (Keijl et al., 2016; Nemet and Johnson, 2012). Doing so would help firms with the generation of recombinant novelty as well as the introduction of breakthrough innovation (Rosenkopf and Nerkar, 2001). Yet, it is unclear the trade-off between the benefit and risks that a firm may incur when generating novelty through their search processes.

Prior empirical studies have mostly focused on demonstrating that exploration was essential to avoid the local search trap, by looking at which external factors increase the exploration process (Laursen, 2012). Only a few studies focused on estimating the actual economic value attached to the search process (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Laursen et al., 2012; Laursen and Salter, 2006), whilst yet no much research on the potential threat of firm search has been carried out. The contention in this thesis is that organisational research needs to take into account both the search process as well as the novelty generated by firm to assess the potential trade-offs undertaken by firms in their pursuit of novelty. Furthermore, the numerous possibilities of the identification of the search processes and novelty reflected by the abundance of information in patents suggest that firm-level analysis should adopt existing indicators to identify novelty through the processes of knowledge-search (Colombelli et al., 2013; Harrigan et al., 2018; Jung and Lee, 2016). The variety of indicators of novelty enriches the information of firm innovation and it encourages the link between knowledge-search and technological novelty.

1. Main Insights

The goal of this dissertation was to move a step forward in the formidable challenge of truly understanding processes of knowledge-search focus by exploring its link with novelty. Several studies have looked at firm processes of knowledge-search for the creation of novel inventions and many indicators of technological novelty have been developed. Generally, the literature describes novelty as the basis onto which economically and technologically influential innovation is generated (e.g. Nelson and Winter, 1982; Schumpeter, 1942). However, not all novel inventions are valuable and not every valuable invention is novel, and the risks and uncertainty are always inherent to the value creation process (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Firms should always carefully balance the outcomes of novelty with the prospect to experience a certain level of risks and uncertainty. The first chapter of this thesis aims to put together and synthesises the distinct concepts of knowledge-search and novelty developed in the literature and to explain their relationship. This chapter combines the theoretical background and operationalisation indicators, for both firm- and invention-level analyses and further compares their empirical finding. The constructed analytical framework intends to assist future studies aiming at understanding the variety of aspects of technological novelty, by serving as a concise and coherent source of information on technological novelty.

The second chapter explores the economic value associated with firm search processes and novelty. The economic impact is assessed through the analysis of the shift in market value after the moment of firms patenting inventions disclosure. In other words, this chapter looks at firm search process from the point of view of investors and aims to inform firms on the perceived value for future growth. Using a sample of around 650 publicly traded US firms from the ICT sector, the empirical analysis reveals that knowledge-search which generates novel recombinations drastically decreases the chances of inventions failures, and exploration which generates novelty significantly increases the invention count of forward citations. This result suggested that novelty could play an important role in the actual economic value of innovation. However, the findings show that novelty has only a marginally positive effect on perceived future value. On the other hand, investors are particularly optimistic about firms expanding their knowledge through exploration processes and this positive expectation increases monotonically. Moreover, the analysis confirms the important role of firm ambidexterity, as this is perceived as the most prosperous firm search strategy. These results need to be cautiously interpreted, as the analysis comprises a number of limitations which are discussed in more detail in the chapter.

Chapter three aims to shed light on the potential risks associated with firm knowledge-search and novelty. The risks are assessed through the investigation of the hazard of firm failure. Interestingly, the role of innovation on firm survival has received surprisingly little attention in the literature, and those few studies that do treat innovation as a black box as the proxies used in the analysis are rudimentary. This study attempts to go deeper into the information of the patenting activity of firms to identify firm knowledge-search, and the novelty processes. Furthermore, this study contributes to the literature by distinguishing exit via bankruptcy from exit via merger/acquisition and controlling for external effects. Using a sample of around 900 publicly traded US firms from the ICT sector, the analysis shows that firm involved with both knowledge-search processes decrease their likelihood of firm failure. However, they are yet prone to exit via merger/acquisition. Ambidextrous firms are however less likely to exit via merger or acquisitions. The role of novelty is yet ambiguous, as this can significantly increase firm failure, whilst it does not increase leverage for merger or acquisition. In contrast, firms that explore are seen as valuable assets thus increase the likelihood of exit via merger or acquisitions.

As highlighted in chapter one, the lion’s share of prior literature has dealt with the technological characteristics of novelty. Yet, a much-neglected aspect of novelty relates to the development of new ideas in the form of novel vocabulary or shift in the existent one (Kuhn, 1962). As such, chapter two contributes to the literature by designing two new indicators of the cognitive characteristics of inventions, and further aims to test breakthrough inventions. Using a sample of all biotechnology patents between 1976 and 200, the analysis indicates, on the one hand, that the vocabulary of radical inventions tends to be substantially different from their prior-art citations, which suggest that novel discoverers may generate the appearance of new words. This chapter develops a further indicator of cognitive novelty which identifies shift in language from a given patent knowledge area using topic modelling. The new indicator detects shifts in knowledge by looking at whether a patent vocabulary is either below or above the average of its assigned topic. Interestingly, inventions with a lower than average topic vocabulary are associated with recombinant novelty, broad and distant technologies, and show cognitive dissimilarity to prior art citations. In contrast, inventions that increase the language above the average of a particular knowledge area are negatively correlated to all the above aspects of novelty. Surprisingly, breakthrough inventions are positively associated with this latter group of cognitive novel inventions. Therefore, shift in knowledge that involve increasing the vocabulary around a specific knowledge area, although negatively associated with technological novelty, yet increase the likelihood of generating breakthrough inventions.

2. Relevance to Practitioners

Firm search process for the creation of novel and valuable inventions, is critical for the long-term success of the firm, beside also contributing to common societal welfare. This comes however with distinct challenges such as, high degree of risk and uncertainty, and costs for example to invest substantially in for the pursue of avenues of exploration for the development of new competences. However, the payoff of these knowledge search processes is in the development of highly novel and breakthrough inventions. This thesis presents two main insights that have clear implications for the recognition and management of knowledge-search practices, and their annexed novelty, and are therefore relevant to practitioners.

Firstly, insight from chapter two suggest that investors respond to *ex-ante* signals of knowledge-search processes and technological novelty. Investors particularly value firms involved in the explorative search process when this is combined with the generation of novel technological recombinations. Practitioners can use these indicators to asses a firm's inventive capabilities to generate diverse and previously unknown technological streams. For example, at the time of acquisition of the explorative firm the assets could help repaying post-acquisitions premiums. Firms may want to use exploration processes to positively influence investor's expectations. Furthermore, practitioners can use these indicators of knowledge-search to evaluate the potential of their own or their competitors' inventions to achieve *ex-post* technological impact.

Secondly, understanding how vocabulary is adopted in relation to technological change may help practitioners through turbulent processes of technological change. Inventions which are cognitive novel may better capture the development of scientific discoveries which may disrupt previous technological paths and they can be the source of competitive shifts in industries. Furthermore, identifying cognitive shift in knowledge would help practitioners understand mechanisms through which new ideas spread over time and space and explain why some new ideas become the wheels of economic fortune (Kaplan and Vakili, 2015), whilst others simply end not long after they born. Identifying cognitive novel inventions may also be useful for effectively managing changes in vocabulary inside their own organisations. Cognitive changes may need the involvement of external expert with distinct knowledge in order to promote innovation.

3. Relevance to Policymakers

The social context of organisational learning is the competitive ecology within which learning occurs and knowledge is used. External competitive processes pit organisations against each other in pursuit of scarce environmental resources and opportunities, such as costumers and governmental subsidies (March, 1991). Technology policies should be directed towards the promotion of resource allocation enabling firms in uncertain technological environments to access external technology competences and enhance exploration/exploitation activities. Doing so may adequately upgrade the overall profitability and marketability efficiency of firms. Following this line of reasoning, the topic of this thesis is highly relevant to policymakers concerned with the nourishment of a healthy and competitive market environment.

This thesis has clearly highlighted the duality of technological novelty as both a saviour and a villain in innovation activities. Technological novelty increases the risks and the uncertainty for the firm, as it is associated to firms patenting failures as well as business failure. However, the pursue of technological novelty is fundamental for the creation of radical innovation and in general for technological progress. This thesis emphasised the need to design specific policy with the aim to reduce the risks and uncertainty for the firm that is bound to the creation of technological novel invention. In particular, policy should be directed to those start-ups that engage in risky exploration activities to increase their chances of generating technological novelty and ultimately radical innovation. For example, this policy could encompass a grant scheme tailored at businesses that have produced technological novel inventions but due to heavy R&D investment face financial instability that may compromise their business survival. In particular, this grant scheme could award those companies that have successfully patented a novel invention with market potential, but do not have the financial means to continue their business activities and they might be forced to sell their technologies and/or business.

The cognitive novelty measures developed in chapter four, will help policy makers to track cognitive novel inventions that may involve scientific discoveries from private companies which development may be discontinued as these may not be economic valuable. In that case, it would be beneficial – under the assumption that shifts in knowledge increase social welfare beyond private returns – to direct policies towards inventions with high cognitive novelty content.

4. Limitations

This dissertation is subject to a number of general limitations. First of all, the findings only extend to innovative activity sensitive to patenting, although not all invention are patented the results cannot account for not patented inventions. Furthermore, whenever in the analysis both the dependent and independent variables consist of information on patent, there may be unobserved factor related to patenting practices which might bias the analysis. As note in prior studies the use of patent classifications to proxy the technological space may have some biases. The USPTO classifications were principally designed to assist patent examiners performing searches. As such, the classification's categories have been created under the subjective assessments of examiners based on their interpretations of the claims and the rules for making classifications (Kaplan and Vakili, 2012). On the other hand, patent documents are rich of informative content and are relatively publicly accessible which makes them the principal choice for the study of innovation.

The topic model approach used in chapter two is subject to a considerable number of limitations. As noted by prior researchers, keywords with different spellings and synonyms increase the likelihood of false negatives, whereas patents with a few keywords which have many different applications across different fields increase the likelihood of false positives. The complexity of words may impact the efficiency of word tokenisation. The number of topics is arbitrary, and patents can be relevant for, and thus being assigned to, several topics at once. Nonetheless, text-mining approaches represent an exciting avenue for future developments and for the support in patent analysis.

5. Avenues for Future Research

There are several areas of this thesis that have significant potential for expansion and further exploration. The first avenue for future research deals with further refine the recombinant novelty indicator for firm-level analysis. This thesis adopted a novelty indicator that considers recombinations at the level of the single invention and then takes the yearly sum of firm patenting activity. However, technological subclasses might have been combined with the subclasses from other inventions of the same patent portfolio. Thus, future research could examine the combinations at the level of the entire patent portfolio of a single firm.

Topic modelling could be adopted to analyse technological distance, ties and spillover between firms, as it was previously carried out using patent classifications or citations between firms. Firms connections could be defined by the topics and the strength of the connections using weight of each topic for each patent. This method could complement patent classes as this tracks the actual language of the actors rather than the classifications assigned by others. Furthermore, topic modelling could be used trace the diffusion of ideas rather than inferring them from citations connections between firms, and this would further allow for the possibility that such connections occur even when particular patents are not cited. Future research could consider more sophisticated similarity measures that consider the number of times certain keywords occurs between patents to identify the strength of their relationship. Furthermore, although the title and the abstract provide the necessary information of the cognitive content of patents, future research could take into account the description of claims or even the full corpus of patents.

6. Contribution and Conclusion

This thesis has attempted to address the complex nature of novelty from a number of different perspectives. Given the time, space and logistical constraints it would be difficult to present a complete portrait of the characteristics and origins of novelty. This thesis has attempted to provide a theoretical and empirical overview of the 'technical' aspect of firm search process for novelty. Although many other processes of search exist this thesis is restricted to only this aspect.

This thesis has made several contributions to the academic literature. It has linked firm-level processes of knowledge-search, and invention-level *ex-ante* novelty indicators, to consider both the value and risks associated with novelty in firm-level analysis. It proposes novel methods to quantify the benefit and challenges associated with novelty. For instance, the economic impact is assessed through the analysis of the shift in market value after the moment of disclosure of patenting inventions. The potential threats are assessed through the investigation of the likelihood of firm's failure.

It has made an empirical contribution to the organisational learning literature as it demonstrated the importance of firm ambidexterity for value-creation and for the management of the associated risks and uncertainty. It supports the tension view of the exploratory search by highlighting that searching unfamiliar knowledge is perceived as more valuable by investors, and it is a useful leverage in merger or acquisitions. Furthermore, this thesis contributes to the literature on survival analysis by highlighting the importance of the distinction between distinct exit procedures, for a more realistic evaluation of the impact of innovation on firm survival.

This thesis contributes to the literature on technological novelty, as it empirically demonstrates the binomial nature of technological novelty by showing that not all novel inventions are successful and that often novelty increases a firm's likelihood of not just patenting failures, but also firm failure. Despite the strong link between novelty and breakthrough innovation, the thesis argues that its tangible economic impact is sporadic and rare, and that it involves substantial risks. This has been highlighted by the empirical evidence which suggests that novelty only marginally encourages investors in further financing of the firm. Lastly, the firm survival analysis has shown that novelty significantly increases firm failure rate, and it does not increase leverage for merger or acquisition.

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