The Impact of Varied Knowledge on Innovation and the Fate of Organizations

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ACADEMIC ABSTRACT

In my dissertation, I examine varied types of knowledge and how they contribute to innovation generation and selection at both the firm and the industry level using the emerging industry context of small satellites. My research is divided into three papers. In Paper One, I take a supply-demand perspective and examine how suppliers of technology—with their unique knowledge of science and technology—and users of technology—with their unique knowledge of demand—contribute to innovation generation and selection over the industry lifecycle. Results show that the contributions of suppliers and users vary based on unique aspects of innovation, such as novelty, breadth, and coherence – and also over the industry life cycle. In Paper Two, I study how firms overcome science-business tension in their pursuit of novel innovation. I examine unique aspects of knowledge: scientists' business knowledge and CEOs' scientific knowledge. I show that CEOs' scientific knowledge is an important driver of firms' novel pursuits and that this impact is higher when scientists do not have business knowledge. In the third paper, I further examine how scientists with high technological and scientific knowledge—i.e., star scientists—impact firm innovation generation and selection. With a focus on explorative and exploitative innovation, I develop theory on the boundary conditions of stars' impact on firm level outcomes. I propose that individual level contingencies—i.e., stage of employment—and organizational level contingencies—explorative or exploitative innovation—both facilitate and hinder stars' impact on firms' innovative pursuits.

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GENERAL AUDIENCE ABSTRACT

In my dissertation, I study innovation at both the firm level and the industry level using the emerging industry context of small satellites. My dissertation divides into three papers. In Paper One, I study unique aspects of innovation at the industry level taking a supply-demand perspective. Since novelty, breadth, and convergence of innovation are all important drivers of the emergence and evolution of industries, I examine how supply side or demand side actors contribute to unique aspects of innovation over the industry life cycle. Results suggest that both suppliers and users of technology make important contributions to innovation, however, their respective contributions vary to novelty, breadth, and convergence of innovation. This impact varies over the industry life cycle. In Paper Two, I study how firms pursue novel innovation as main creator of economic value for firms. Firms need both scientific and technological knowledge in their pursuit of novel innovation. However, firms often struggle to overcome science-business tensions. Focusing on CEOs and scientists as two main drivers of innovation, I study how CEOs' scientific knowledge and scientists' business knowledge help firms overcome business-science tension. Results suggest that the likelihood of firms' novel pursuit is higher when CEOs have scientific knowledge and scientists do not have business knowledge. In Paper Three, I further examine how high-performing scientists—i.e., star scientists—impact explorative and exploitative innovation. I propose that the stage of employment of individuals and goal context of firms are important contingencies that impact how stars impact firm level innovation.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

In my dissertation, I study multi-level mechanisms impacting the *generation* and *selection* of innovation. Innovation is an important driver of sustainable competitive advantage (e.g., Eisenhardt & Tabrizi, 1995), economic value (Kaplan & Vakili, 2015), and emergence of new industries (Moeen & Agarwal, 2017; Schumpeter, 1942). Thus, scholars have long tried to determine different aspects of innovation and their sources at the firm and the industry level (e.g., Baba, Shichijo, & Sedita, 2009; Moeen, 2017). The processes supporting the generation of innovation form a path that spans the generation of new ideas to the selection of ideas for commercialization (Nemet, 2009). I theoretically ground these processes of innovation and examine their drivers.

I focus on three aspects of innovation generation: exploration, novelty and breadth of innovation. Exploration refers to the search for knowledge beyond existing technological knowledge (March, 1991). It is an important aspect of innovation generation because firms need to explore new knowledge domains in order to move beyond their current technological trajectories (Kogut & Zander, 1992). Novelty of innovation refers to the introduction of a potentially new technological trajectory, in contrast to incremental innovation which largely follows existing trajectories (Kaplan & Vakili, 2015). Novelty is important as firms need to generate new, valuable ideas and to explore original solution sets (Ahuja & Lampert, 2001). Breadth refers to the diversity of innovation and is also notable as it shows the variety of unique solution sets to address problems (Hunt, 2018), and provides the possibility of addressing wider variety of needs in the market.

To examine selection of innovation, I focus on exploitative innovation and coherence of innovation. Exploitative innovation refers to leveraging opportunities within current technological domains (March, 1991). Firms pursue exploitative innovation to use their current technologies and benefit from their established lines of business (Christensen, 1997). Coherence of innovation refers to convergence in the understanding of technologies and agreement on designs (Kretschmer, 2008). Coherence acts as a driver of commercialization (Suarez, Grodal, & Gotsopoulos, 2015). Focal phenomena of interest and how they are addressed in each paper of the dissertation are shown in Figure 1-1.

[Insert Figure 1-1 about here]

In order to generate innovation, firms must recombine knowledge in novel ways (e.g., Kogut, & Zander, 1992), which has led many scholars to suggest that knowledge is the main contributor to innovative advancements in firms (e.g., Kaplan & Vakili, 2015) and the emergence of industries (Krafft, 2004). I focus on different types of knowledge, theorize complementarities and tensions between them, and explain how they contribute to innovation generation and innovation selection at both the firm and industry levels. At the firm level, I theorize how scientific and technological knowledge possessed by scientists and CEOs impact innovation generation and illuminate how science-business tensions in the innovation generation process are navigated and overcome. Additionally, since scientists have long been known as main contributors to innovation (Subramanian, Lim, & Soh, 2013), I theorize the roles and limits of scientists in the process of innovation generation and selection, connecting the human resources literature to innovation and strategy. I focus on scientists who possess high levels of scientific and technological knowledge — i.e., star scientists — and explain the mechanisms through which they affect the generation and selection of innovation.

At the industry level, I address unique types of supplier knowledge and user knowledge and how they contribute to the generation and selection of innovation. I extend past scholarly efforts by incorporating a demand-side perspective in my theorizing (Priem, Li, & Carr, 2012).

Despite scholarly recognition that users are important, their impact has not been incorporated to the heavily supply-oriented industry evolution literature. To illuminate contingencies governing the relationship between knowledge types and innovation generation and selection, I identify temporal shifts and theoretically lay them out at different levels of analysis (i.e., industry life cycle at the industry level and employee life-cycle at the individual level).

I chose the small satellite industry as the empirical context for my dissertation due to its emerging and highly technological nature. In emerging, high-technology industries with a high level of convolution (Eggers, 2014; Townsend, Hunt, McMullen, & Sarasvathy, 2018), the process of generating and selecting innovations is highly complex. The small satellite industry emerged with the launch of Sputnik 1 (84 Kilograms), Explorer 1 (14 kilograms), and Vangaurd 1 (14 kilograms) in 1957 and 1958 (Helvajian & Janson, 2008; Rivers, 2015). In 1981, the first modern microsatellite – UoSat 1 was successfully launched. In 1992, satellites started to be grouped based on their size, and in 1999 the dominant design of CubeSat was developed by university professors (Deepak & Twiggs, 2012). This industry has grown tremendously in the last couple of years, with 53% increase in satellite launches from 2012 to 2017 (average of 144 launches per year) (Satellite Industry Association Report, 2017).

The small satellite industry is an ideal context for my dissertation for a number of reasons. First, this industry provides a great setting to examine unique aspects of innovation generation (i.e., novelty and breadth) and innovation selection (i.e., coherence). The small satellite industry emerged with the introduction of novel technologies where novelty is an important innovative endeavor especially for many nascent stage firms that entered the industry. Breadth of innovation can be seen in very broad applications of small satellites, especially with advanced data analytic techniques (Song, 2017). For instance, many firms use satellite data for stock price prediction, oil price prediction, weather, etc. Also, the importance of coherence of innovation can be seen in the initiation of industry specific conferences such as Small Satellite Conference in 1987. These conferences provide a setting for knowledge exchange to create convergence and some level of agreement on the technologies and their uses.

Second, many key industry events are driven by a combination of supply push and demand pull forces (such as Educational Launch of Nanosatellites by NASA), suggesting that user demand is a key determinant of innovative pursuits in the industry. Inception of industry specific conferences such as Small Satellite Industry Conference and American Institute of Aeronautics and Astronautics (AIAA) shows the importance of collaboration, interaction, and co-creation between suppliers and users in the emergence and evolution of the industry. Additionally, this industry has faced much convolution, including a considerable slump in the late 1970s and early 1980s. This trend was reversed by technological and economic conditions and users' activities. For instance, AMSAT (Radio Amateur Satellite Corporation) pursued innovative activities for educational and experimental launches of small satellites during the "doldrums" years because of small satellites' low cost and high level of sophistication (Janson, 2011). This contributed significantly to reversing the downward trend in the industry at that time, suggesting that demand forces are important in both the generation and selection of innovative choices, and their impact is likely to differ at various stages of the industry life cycle.

Third, according to industry experts, many founders and CEOs show high passion for exploring space and scientific advancements; despite most profit accruing from the operation and usage of satellite data (Song, 2017). This suggests that there is great tension between scientific advancements and economic goals in the small satellite industry. It is therefore a highly suitable context for exploring business-science tension, especially when there is a need for both pursuing novel innovation and generating profits. Finally, this industry is rapidly evolving. This generates a context where firms, especially nascent participants, must address business and scientific tensions in a timely manner. Taken together, this high technology and emerging industry with many nascent stage firms is highly appropriate for examining how innovation is generated and selected at both the firm and the industry level.

My dissertation is broken into three papers, where Paper One and Paper Two are empirical and Paper Three is conceptual. Below, I provide more details on each.

Paper One

In Paper One, I take a supply-demand perspective and theorize how providers of technology (with unique technological knowledge) and users of technology (with unique knowledge of demand) contribute to innovation generation and innovation selection over the industry life cycle. Literature on how industries emerge and evolve has long been oriented toward the supply perspective, which looks "inside" firms (Priem et al., 2012: 347), and focuses on their resources, capabilities, and technological knowledge (Eggers, 2012, 2014; Krafft, 2004; Sanderson & Simons, 2014). Focusing on the suppliers of technology has resulted in gaps in our understanding of the important contributions of consumers (i.e., end users) and customers (i.e., intermediary firms in the industry) (Priem et al., 2012).

I theorize that innovation generation is a result of interaction and knowledge exchange among variety of actors on both the supply side and demand side of the industry (Adams, Fontana, & Malerba, 2013; Brown & Eisenhardt, 1995; Malerba, 2002). I explain how suppliers and users of technology contribute to unique aspects of innovation generation (i.e., novelty and breadth of innovation) and innovation selection (i.e., coherence) – each of which is important in the birth and evolution of industries. Specifically, I propose that novelty of innovation is the main driver of change (Kaplan & Vakili, 2015) and emergence of industries; breadth of innovation shows diversity of solution sets (Brown & Eisenhardt, 1995) and drives maturity of industries; and coherence in innovation is a driver of commercialization (Suarez et al., 2015) and growth of industries.

I analyze a novel dataset of papers presented at the Small Satellite Conference, the most important conference of the small satellite industry using machine learning techniques (i.e., topic modeling) (Blei, Ng, & Jordan, 2003). Results are illuminating in several ways. First, both suppliers and users drive novelty, and users are more important in earlier stages of the industry emergence. Second, demand plays a more substantial role in enhancing breadth of innovation. This finding implies that developing interactive learning mechanisms with customers can create more opportunities for suppliers of technologies to develop wider set of innovative solutions. Third, some level of involvement of users is the most effective in creating coherence. This shows that supply and demand co-create convergence and agreement in the process of innovation selection. As the results of this paper suggest different types of knowledge make unique contributions to innovation generation and selection.

Paper Two

Findings of Paper One motivate Paper Two, in which I investigate the business-science tensions in firms and examine how the unique types of knowledge possessed by scientists and CEOs (the two main drivers of innovation) impact innovation generation. Prior research has mainly focused on the technological knowledge of scientists as important driver of innovation (e.g., Baba et al., 2009; Subramanian et al., 2013). I challenge the widespread view that scientists lack business knowledge and examine how their business knowledge impacts firms' novel innovation. On a separate path, scholars have examined the role of upper echelons on firms' innovation (Cho & Kim, 2017; Park & Tzabbar, 2016), as they direct and lead innovative activities of firms (Conti, Gambardella, & Mariani, 2013). Although some CEOs are scientists, prior research has ignored how CEOs' scientific knowledge impacts firms' novel innovation. I examine how CEOs' scientific knowledge impacts firms' novel innovation.

I build on these two largely independent streams and theorize that, although pursuit of novel innovation requires both business and scientific knowledge, often, these bodies of knowledge or their sources are not necessarily compatible. Indeed, a key reason that firms struggle in novel pursuits is the misalignment of economic and business goals on one hand, and scientific goals on the other hand (Christensen, 1997). I examine the direct and intertwined impact of CEOs' scientific knowledge and scientists' business knowledge on firms' novel pursuits. I argue that interactions between CEOs and scientists tend to have important implications for overcoming the science-business tensions associated with firm innovation. Using textual data of NASA grants and papers presented at the Small Satellite Conference, my results suggest that CEOs' scientific knowledge increases the likelihood of novel pursuits, with a more positive impact when scientists do not have business knowledge. This insinuates that probability of novel pursuits is higher when knowledge gap between CEOs and scientists is filled by CEOs' scientific knowledge, and not with both CEOs' scientific knowledge and scientists' business knowledge.

Paper Three

In Paper Three, I delve into the impact of high-performing scientists with high levels of scientific and technological knowledge on firms' innovation generation and selection. Specifically, I examine how star scientists impact explorative (i.e., an aspect of innovation generation) and exploitative (i.e., an aspect of innovation selection) innovation in firms. Stars are rare, high-achieving individuals who deliver unmatched levels of innovative value (Helft, 2011; Kehoe &

Tzabbar, 2015). Literature on stars has largely reinforced the perception that stars are indispensable to firm vitality and innovative endeavors (Aguinis & O'Boyle, 2014; Boynton & Fischer, 2005; Wright, Coff, & Molierno, 2014). However, recent scholarly work also suggests stars do not always produce desirable results and reveals counterproductive, counterintuitive facets of star systems (e.g., Asgari & Hunt, 2015; Kehoe & Tzabbar 2015). These inconsistencies in the literature suggest that more nuance is required to study how stars impact firm-level outcomes.

In order to provide useful boundary conditions regarding how stars impact firm-level outcomes, I theorize that the *stage* of employment (representing the evolving organization-employee level of fit) and *goals* of a firm (showing specific mechanisms and skills required) explain stars' impact on organizational innovation. My paper develops a contingency-based framework that accounts for two vital dimensions. I propound the notion that the facilitators and inhibitors of stars' effectiveness are likely to differ based on the evolving nature of the organization-employee fit (Allen, 2006; Smither, 2003), and the goals that firms pursue (Groysberg & Lee, 2009; Tzabbar & Kehoe, 2014).

Contribution

Taken together, my dissertation systematically investigates multi-level mechanisms of innovation generation and innovation selection. I theorize tensions and complementarities between unique knowledge types: business knowledge and scientific knowledge at the firm level, and technological knowledge and user knowledge at the industry level. Figure 1-2 outlines the overarching conceptual model of the dissertation and the focus of each paper, resulting in a number of important contributions.

[Insert Figure 1-2 about here]

First, my dissertation contributes to the literature on industry evolution by uniquely incorporating demand-side perspective. I explain how users and suppliers of technology contribute to different aspects of innovation over the industry life cycle. Moreover, I provide empirical evidence on the importance and uniqueness of users contributions to innovation generation and selection at different stages of industry emergence and evolution. Thus, it sheds light on how industries emerge and evolve.

Second, I contribute to the innovation literature by theorizing about the unique aspects of innovation generation and innovation selection, and theoretically mapping them at the firm level and the industry level. At the industry level, I identify novelty, breadth, and coherence of innovation as unique aspects of innovation generation and innovation selection that contribute to industry emergence and evolution. Empirical evidence suggests that knowledge of suppliers and users makes unique contributions to each aspect of innovation generation and selection. At the firm level, I explain how firms generate and select innovation. I theorize how business and scientific knowledge distributed within firms plays an important role in overcoming business-science tensions associated with novel innovations. More specifically, I articulate how CEOs' scientific knowledge and scientists' business knowledge independently and jointly impact firms' novel pursuits, illuminating how tensions between business knowledge and scientific knowledge are addressed in firms' novel pursuits. The empirical results are enlightening with regard to the significance of CEOs' scientific knowledge, in particular as it relates to firms' generation of novel innovation.

Third, my research develops limits and boundaries concerning the impact of star scientists who possess high levels of scientific and technological knowledge on firms' generation and selection of innovation. I theorize that the evolving nature of employee-employer relationship is an important indicator of how stars impact firms' generation and selection of innovation; thereby connecting the human resource management literature with the strategy and innovation literature. My research provides boundary conditions that govern the favorable and unfavorable impact of stars, while advancing a theory of "non-uniformity," a predictive basis that accounts for changes in the organization-star relationship over time and models stars' impact as a function of the manner in which organizations pursue innovation.

Fourth, in addition to theoretical and empirical contributions, my dissertation makes important methodological contributions. It shows how machine learning and text analytic techniques can be used in the strategy field to analyze large numbers of textual documents, and facilitate development of new measures and new approaches to data analysis. I develop new measures of innovation in my dissertation, showing the possibility of developing unique applications of such techniques. Also, it shows how unique sources of data, such as textual content of grants and papers, can be used to examine emerging contexts that lack established sources of data. My application of unique data sources reveals new empirical approaches for addressing challenging and complex puzzles in the strategy and innovation literature.

Summary

Overall, my results demonstrate that multiple contingency factors govern the impact of different types of knowledge on innovation generation and selection. At the firm level, the impact of different types of knowledge on innovation depends on the role of individuals who possess the specific knowledge type, the evolving nature of the relationship between employee and employer, and the goal context of the firm. At the industry level, my research shows that the contribution of unique supplier and user knowledge varies based on different aspects of innovation, and different stages of industry life cycle.

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Figure 1-1 Focal Phenomena of Interest

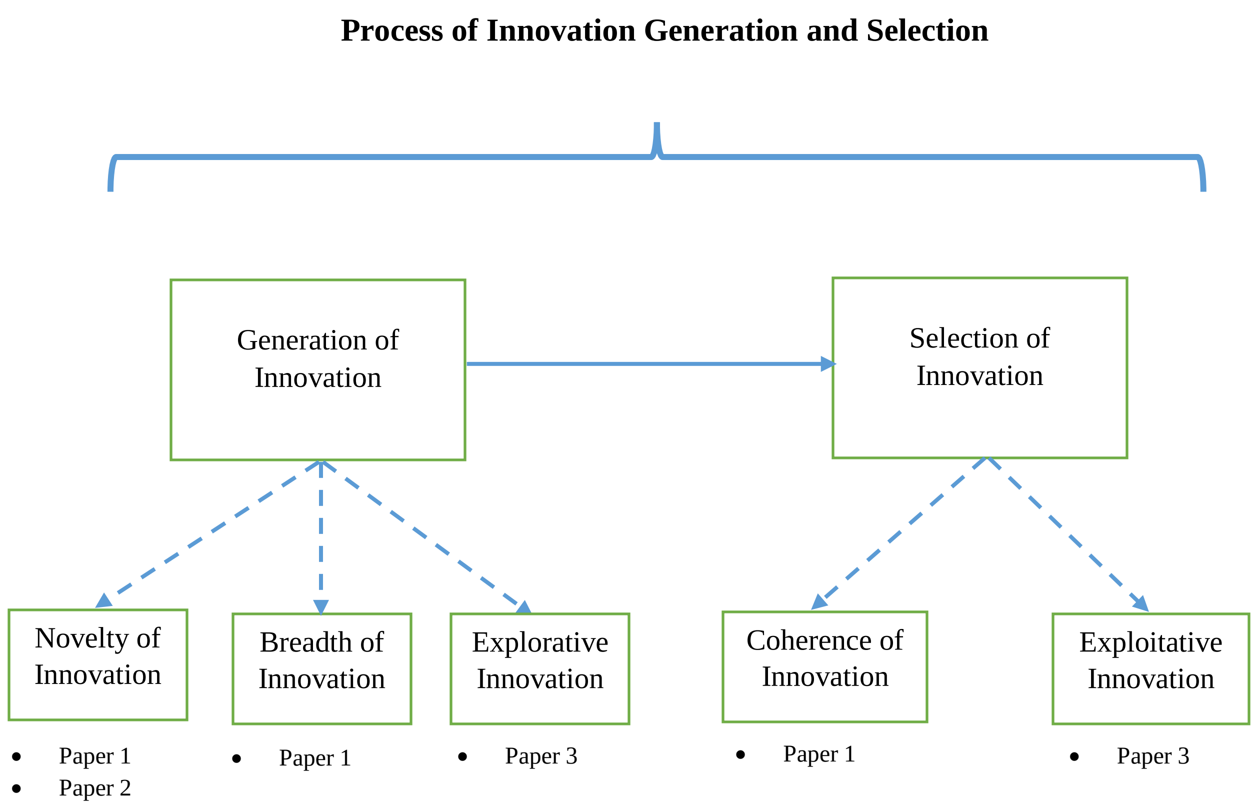
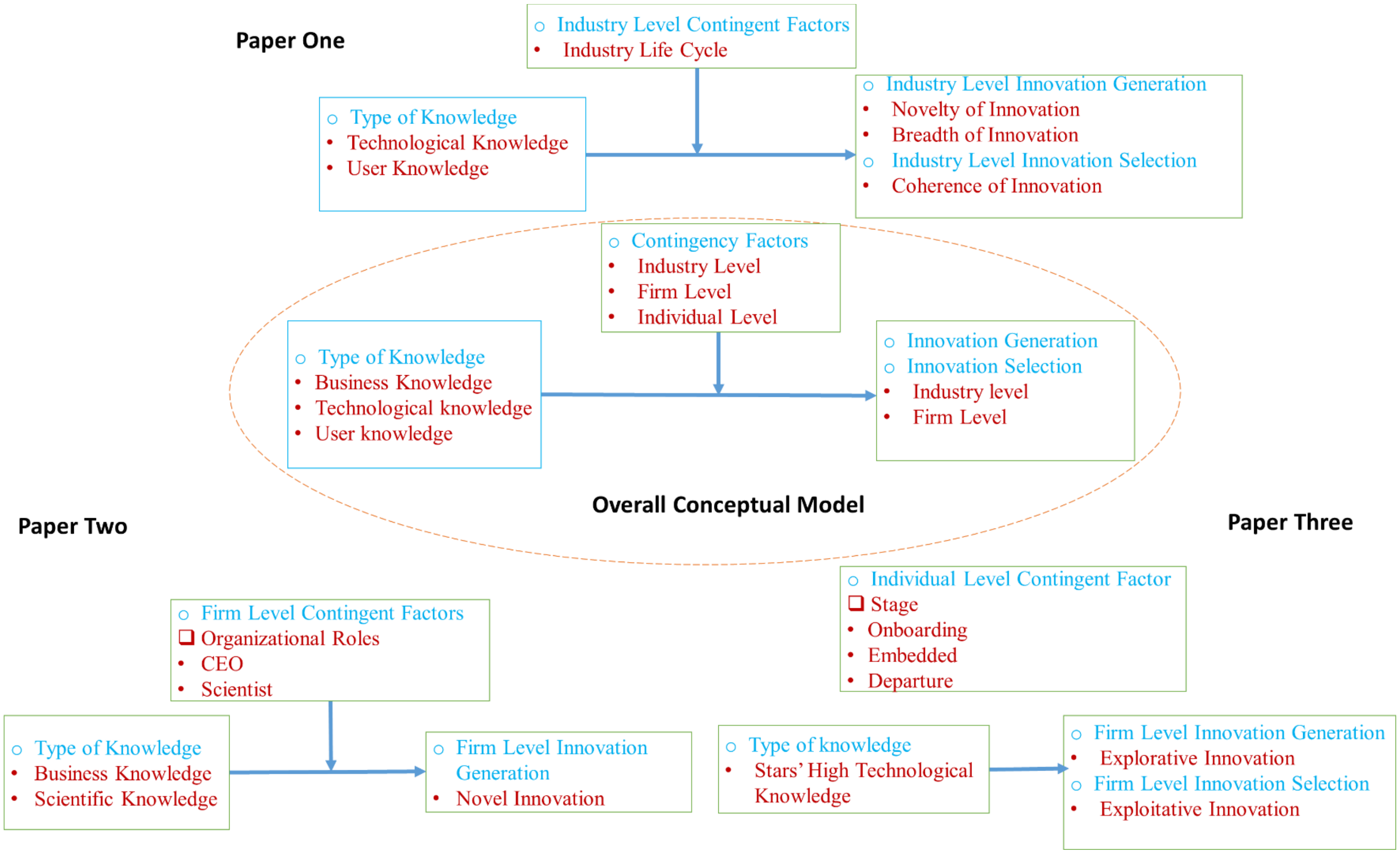


Figure 1-2 Overall Conceptual Model of the Dissertation



CHAPTER 2: PAPER ONE

EVOLUTION OF AN INDUSTRY: EXPLORATION OF DISTINCT ROLES OF DEMAND PULL AND TECHNOLOGY PUSH IN INNOVATION IN THE SMALL SATELLITE INDUSTRY

2.1 INTRODUCTION

The literature on industry evolution is predominantly supply oriented. The supply perspective has mostly looked "inside" the firms (Priem, Li, &, Carr, 2012: 347), with a focus on resources, capabilities and firms' technological knowledge (Eggers, 2012, 2014; Krafft, 2004; Sanderson & Simons, 2014). Emphasizing the role of scientific and technological advancements (e.g., Adner & Kapoor, 2016; Eggers, 2012, 2014; Krafft, 2004; Sanderson & Simons, 2014), researchers have examined how players in an industry with heterogeneous resources and capabilities contribute to innovation generation as industries emerge and evolve (e.g., Adner & Kapoor, 2016; Moeen & Agarwal, 2017). The central point in understanding innovation generation over the life cycle of the industry has been on technological choices that firms make (e.g., Furr & Kapoor, 2018), the knowledge context that firms come from (e.g., Agarwal & Shah, 2014; Benner & Tripsas, 2012), or firms' capabilities (e.g., Furr & Kapoor, 2018; Moeen & Agarwal, 2017). Most of the work on industry evolution has focused on "technology-push" – where technological knowledge and resources are the drivers of innovation – and its impact on patterns of knowledge and innovation generation. However, the literature has paid limited attention to and minimized the role of demand-pull – where innovation is driven by demand in the external environment.

Research suggests that innovation is a result of interaction and knowledge exchange among many actors (Adams, Fontana, & Malerba, 2013; Malerba, 2002) – a wide variety of organizations including firms that provide equipment and technology, universities and research institutes, and consumers and customers of technologies. The interaction among these players on both the supply and the demand side of the industry is highly prominent in fast-paced, high technology industries (Brown & Eisenhardt, 1995). Knowledge generation, accumulation, exchange, and evolution are the main drivers of industry emergence and evolution (Krafft, 2004; Krafft, Lechevalier, Quatraro, & Storz, 2014). Until now, researchers have focused on knowledge generation and exchange by actors on the supply side of the industry, and largely ignored the significant contributions of demand from consumers (i.e., end users) and customers (i.e., intermediary firms in the industry) (Priem et al., 2012). Although recent scholarly work has attempted to underscore the consumers' and customers' knowledge in driving innovation (e.g., Adams et al., 2013; Hunt, 2018), there is little empirical work examining *how* knowledge of consumers and customers contributes to innovation generation and selection over the industry life cycle. This has resulted in a lack of understanding and an underestimation of their contribution in shaping the industry evolution.

Addressing this gap, I investigate to what extent and how technology-push (i.e., created by supply-side forces) and demand-pull (i.e., created by demand-side forces) contribute to *innovation generation* and *selection* over the life cycle of an industry. I argue that both supply and demand have distinct and significant contributions to the knowledge base of an industry and innovation generation and selection over the industry life cycle. The process of innovation consists of a path from the generation of ideas to the selection of those ideas (Nemet, 2009). I specifically investigate unique aspects of innovation to examine to what extent breadth of innovation and novelty of innovation (as essential aspects of innovation generation), and convergence (as critical aspect of innovation selection) supply and demand create as industries emerge and evolve. These unique aspects of innovation are integral to generating insight into how suppliers and customers and consumers contribute to innovation and the emergence and evolution of an industry. *Breadth of* *innovation* shows varied solution sets to address problems (Brown & Eisenhardt, 1995; Hunt, 2018). *Novelty of innovation* is the primary driver of change in technological and scientific innovations and creates economic and social value (Kaplan & Vakili, 2015; Kuhn, 1970; Phene, Fladmoe-Lindquist, & Marsh, 2006). *Coherence of innovation* refers to convergence in the understanding of technologies and agreement on designs (Kretschmer, 2008). Coherence acts as a driver of commercialization (Suarez, Grodal, & Gotsopoulos, 2015).

I focus on a high technology context – the small satellite industry. This industry provides an ideal setting to examine novelty, breadth, and coherence of innovation. The small satellite industry emerged with the generation of novel technologies. Novelty is an indispensable part of the small satellite industry, especially for nascent stage firms because it serves as an indispensable indicator of success. Breadth of innovation can be seen in very broad applications of small satellites, especially applications that are developed with advanced data analytic techniques (e.g., using satellite data for stock price prediction, oil price prediction, weather, etc.). The importance of coherence is apparent in key events within the industry (e.g., initiation of industry-specific conferences like the Small Satellite Conference that shows the need for agreement on designs and technologies). I use a novel dataset of all the papers presented in the most attended conference of the industry spanning over 30 years. I use a text mining technique—i.e., topic modeling—to study the contribution of supply and demand by analyzing rich textual documents of scientific papers. Structural topic modeling (Roberts, Stewart, Tingley, & Airoldi, 2013) is introduced as a useful method to investigate my research questions. This method enables me to inductively identify scientific and technological topics and provides a basis to analyze novelty, breadth, and coherence of those topics.

This study makes three important contributions. First, it advances the literature on industry emergence and evolution by illuminating the importance of the supply-demand perspective (Agarwal, Echambadi, Franco, & Sarkar, 2004; Furr & Kapoor, 2018; Moeen & Agarwal, 2017). Previous research has remained silent on how the demand side of the industry contributes to innovation. This study sheds light on how different actors in an industry contribute to innovation generation and innovation selection, and consequently, industry emergence and evolution. Empirical results suggest that demand is an important contributor to how industries emerge and evolve. Second, this study contributes to the literature on demand-side perspective (Hunt, 2018; Priem, 2007; Priem et al., 2012; Sidhu, Commandeur, & Volberda, 2007), by showing how consumers and intermediary firms and institutes contribute to innovation generation and selection. Despite limited attempts to examine the contribution of customers at the sectoral level (e.g., Adams et al., 2013), we do not have a clear understanding of the importance and nuances of how the demand-side drives innovation – in terms of novelty, breadth, and coherence of innovation. This study provides empirical evidence on how and to what extent customers are important in innovation generation and selection over the industry life cycle.

Finally, beyond theoretical and empirical contributions, this study proposes structural topic modeling (Roberts et al., 2013) as an effective method to benefit from rich sources of data that had previously been underutilized. Prior studies have mainly used patent classes, patent citations, SIC codes, or number of patents and papers as really crude measures (Bernardes & Albuquerque, 2003), with their own drawbacks (Aharonson & Schilling, 2016). I demonstrate how scholars can benefit from large numbers of textual data and from inductive and deductive methods to answer research questions that require large data analysis (this is especially important in emerging industries that lack established sources of data.).

In what follows, first, I review the literature and propose hypotheses to address questions that elaborate on research gaps in the literature. Second, I present a new methodological approach to test the hypotheses. Third, results, discussion and implications of research are presented.

2.2 LITERATURE REVIEW

Industry Evolution

New industries are created following creative destruction (Schumpeter, 1942) or knowledge accumulation (Krafft et al., 2014; Loasby, 1999) and are associated with high entrepreneurial entry of firms (Moeen & Agarwal, 2017). After industries emerge and go through the paths of shakeout, they start to grow and evolve (Furr & Kapoor, 2018; Rothaermel, 2015). The dynamics by which industries are created and developed are crucial to understand the evolutionary patterns of capitalist economies (Krafft et al., 2014). Emergence and evolution of industries have been studied along different trajectories. One set of studies has focused on path dependent knowledge creation, and how it has evolved and contributed to the evolution of an industry. This is because knowledge is the key to the process that helps industries emerge and evolve (Krafft et al., 2014; Loasby, 1999; Schumpeter, 1942). As Krafft et al. (2014) argue the process of the emergence of industries is shaped by dynamics of knowledge creation. This stream of literature has mainly focused on technological knowledge provided by supply-side and producers in the industries (e.g., Adner & Kapoor, 2016; Colombelli, Krafft, & Quatraro, 2014; Eggers, 2012, 2014; Geels, 2004; Grodal, Gotsopoulos, & Suarez, 2015; Kapoor & McGrath, 2014; Sanderson & Simons, 2014). For instance, Eggers (2012, 2014) investigated how choosing winning and losing technologies impacts the knowledge base and abilities of firms and how the choice of technologies has path dependent impacts on firm outcomes. Colombelli et al. (2014: 1681), investigating regional industries, showed that "the technological competences accumulated at the local level are likely to shape the future patterns of technological diversification." Krafft (2004) emphasized on the role of knowledge and how knowledge generation and diffusion impact patterns of entry in the industry of information communications.

All these studies point out to the importance of knowledge diffusion, path dependency in knowledge evolution, and central role of the knowledge of providers of technology in creating and driving industries. As it can be seen, most scholarly works have taken a supply-side or technology-push approach (e.g., Eggers, 2012, 2014; Colombelli et al., 2014; Huenteler, Ossenbrink, Schmidt, & Hoffmann, 2016; Lechevalier, Nishimura, & Storz, 2014; Moeen & Agarwal, 2017; Sarkar, Echambadi, Agarwal, & Sen, 2006). On the other hand, recently researchers (mainly outside the industry evolution literature) highlight the importance of the role of demand-pull in entrepreneurial activities, knowledge generation, and innovation (e.g., Adams et al., 2013; Hunt, 2018). Noticeably, the role of demand-pull is understudied in scholarly works on industry evolution and its driving forces, and its contribution is underestimated. Table 2-1 provides the summary of the literature on the industry evolution literature that has primarily focused on technology-push. In what follows, I provide the literature review on demand side perspective and the importance of its incorporation to the industry evolution literature.

[Insert Table 2-1 about here]

Technology Push/Demand Pull

The literature on innovation, knowledge generation and strategic management is predominantly driven by the focus on suppliers as the primary providers of technology (e.g., Eisenhardt & Martin, 2000; Lockett, Thompson, & Morgenstern, 2009). The approach that this stream of research has taken is to look at drivers of innovation focusing on firms’ resources and capabilities, scientific and technological knowledge, and founders' characteristics (Barney, 1991; Di Stefano, Gambardella, & Verona, 2012; Romanelli & Schoonhoven, 2001). However, there is recent scholarly work trying to explore the role of customers and consumers. This emerging stream has mainly remained at the firm level (Priem et al., 2012), and attempted to point out to the importance of heterogeneity of customers in how firms respond to technological change, or how customers' preferences impact firms' strategies, value creation, and value capture (e.g., Adner & Snow, 2010a, 2010b; Priem, 2007).

Despite the emergence of this stream of research, the importance of the demand on value creation and innovation generation has remained under-noticed in the industry evolution literature. Understanding the role of demand is of great importance because there are multiple kinds of firms, universities, and research institutes that innovate and create value for consumers – which refer to end users – and customers – which refer to intermediary firms in the industry (Priem et al., 2012). Demand-side perspective mainly focuses on external environment of firms by looking downstream at consumers, customers, and product markets (Priem et al., 2012).

In a high-tech context, where innovation is the main driver of the emergence and evolution of industries (Schumpeter, 1942), there is a debate on whether technological breakthroughs or market demands drive the industry. This debate is mainly referred to technology-push vs. demand-pull (Di Stefano, Gambardella, & Verona, 2012; Rosenberg, 1982; von Hippel, 1976). As Priem et al. (2012) argue there are many perspectives that have reinforced the technology-push perspective, most importantly resource based view and disruptive technology. Resource based view of the firm has emphasized on firms' internal technological capabilities and resources, and got much attention as primary explanation of innovation (Benner & Tripsas, 2012; Hoskisson, Hitt, Wan, & Yiu, 1999). Also, Christensen (1997) introduced disruptive technologies, pointed out to the failure of incumbents to adopt such technologies because of their focus on customers, and further contributed to technology push perspective. Relatedly, there is research showing that demand-pull perspective is not able to prove its importance. As Dosi (1982: 150) put it, demand-pull perspective has not succeeded "to produce sufficient evidence that 'needs expressed through market signaling' are the prime movers of innovative activity". As Di Stefano et al. (2012: 1284) put it, "Overall, science and technology seemed to be 'the' source for the vast majority of technological innovations and demand was the best companion to drive innovation in the right economic and institutional directions."

Although there is great emphasis on technology-push perspective and its role in driving innovation, there is scholarly work pointing out to the importance of demand-side forces. For instance, it has been shown that interaction between supply and demand has a positive impact on innovation (Kalcheva, McLemore, & Pant, 2018; Kline, Rosenberg, & Landau, 1986). Concepts like "open source innovation" (Baldwin & von Hippel, 2010; von Krogh & von Hippel, 2006), "collaborative innovation with customers" (Lettl, Herstatt, & Gemuenden, 2006; Nambisan & Baron, 2010), or "users as innovators" (Bogers, Afuah, & Bastian, 2010) show the importance of customers and consumers in explaining and driving innovation. This shift towards the demand-pull drivers of innovation and performance (Baldwin & von Hippel, 2010) has caused debates between the two perspectives on innovation.

Majority of the research on demand-side factors has been done at the firm level (Priem et al., 2012), while the impact of such forces at the industry level is understudied. For instance, Corrocher and Zirulia (2010) showed that especially when uncertainty is high the information and incentives that user behavior provides are particularly important in innovative strategies that firms choose. Fabrizio and Thomas (2012) emphasized on the role of local demand in specifying the pattern of innovation over and above the role of technological knowledge spillover in global industries and for multinational companies. Sidhu et al. (2007) emphasized on the role of demand-side search on innovation in less dynamic environments. Similarly, Pellegrino and Savona (2017) showed that demand, especially in concentrated markets, is as important as financial factors in specifying firms' innovative failures. In addition to innovation, demand has been shown to be important in creating sustainable competitive advantage for firms (Adner & Zemsky, 2006), competitive dynamics (Adner, 2002), and firms' strategies such as diversification or backward integration (Mawdsley & Somaya, 2018; Priem, 2007). Similarly, Adner and Snow (2010a, 2010b) evaluated heterogeneity among firms' customers and examined its impact on firms' strategic responses to radical technological changes.

In addition to the work examining demand at the firm level, there are few scholarly works pointing out to the importance of demand in relatively few industries or countries. There are multiple players in industries to drive innovation including end users and intermediate user firms (Malerba, 2002). These actors contribute to innovation by the feedback and solutions they provide, or the knowledge of application and needs (Adams et al., 2013; Baba, Shichijo, & Sedita, 2009). For instance, Malebra (2004) and Mowery and Nelson (1999) showed the role of demand in different countries on driving innovation in semiconductor industry. Other studies examined the role of demand in various industries such as ICT, computer, motorcycles, or chemical industries (Lüthje, 2004; Malerba & Mani, 2009; Mowery & Nelson, 1999). Adams et al. (2013) compared the magnitude of the patents generated by user and intermediary firms in comparison to suppliers in semiconductor industry. The contributions of 'lead' users through the solutions they provide for specific needs they identify in advance of the market (Urban & von Hippel, 1988), and user entrepreneurs through commercialization of the products and services have been emphasized in this stream of literature (Hienerth, 2006; Shah & Tripsas, 2007). Also, Hunt (2018) showed the importance of latent societal demand on entrepreneurial innovation by using archival data which spanned around a century.

Despite these attempts to understand the role of demand, it is not clear how demand forces contribute to the innovation generation and selection in industries over the industry life cycle. There are important questions that remain unanswered: What drives industry emergence and evolution? How much novelty, breadth, and coherence do supply and demand create over the life cycle of an industry? These questions are important to answer because innovation, as the main driver of industries, has multiple aspects that have been emphasized in the literature (e.g., Brown & Eisenhardt, 1995; Conti, Gambardella, & Mariani, 2013; Eggers, 2012, 2014; Hunt, 2018; Tzabbar, & Margolis, 2017). Literature has shown that novelty of innovation is the main driver of change (Kaplan & Vakili, 2015) and emergence of industries; breadth of innovation shows diversity of solution sets (Brown & Eisenhardt, 1995) and growth of industries; and coherence of innovation is the driver of commercialization (Suarez et al., 2015) and maturity of industries. This leaves opportunities for examining the role of demand at the industry level. The aim of this paper is to examine the breadth and novelty of innovation (essential aspects of innovation generation) and coherence of innovation (critical aspect of innovation selection) by demand-side and supply-side of an industry. Since actors on each side has unique capabilities, knowledge bases, and goals in the industry, supply and demand forces are likely to have distinct impacts on different aspects of innovation. In addition, as pointed out by Priem et al. (2012) most of the demand-side research is qualitative especially for nascent stages of firms' formation. However, there are opportunities for using quantitative methodologies to advance the field. In the following section, I provide the hypotheses I develop based on the literature and propose a new method to test the hypotheses.

2.3 THEORY DEVELOPMENT AND HYPOTHESES

Technological advancements in industries are created by collective efforts of supplier firms, universities, research organizations, government, and intermediary (i.e., customers) or user firms (i.e., consumers). Each of these players makes essential contributions to knowledge and innovation generation over the life cycle of the industry. Although both supply and demand are important contributors to knowledge base and innovation generation in industries (Chidamber & Kon, 1993; Mowery & Rosenberg, 1979), it is not clear how they contribute to innovation generation of industries in terms of novelty, breadth, and coherence. In what follows, I point to the understudied role of demand and discuss how demand and supply contribute to innovation generation.

Novelty of Innovation

Novel innovation refers to a type of innovation that "introduces a potential new technological trajectory" instead of following on existing technological trajectories (Kaplan & Vakili, 2015: 1436). Novelty of innovation is crucial in driving the technological advancements in industries; novelty creates the driving force of change in scientific and technological trajectories, and generates economic value or develops diversification opportunities (Ahuja, Coff, & Lee, 2005; Benner & Tripsas, 2012; Hall, Jaffe, & Trajtenberg, 2005; Kuhn, 1970, 1996; Phene et al., 2006). Although the dominant view is that demand-side is associated with the generation of more incremental innovation (Mowery & Rosenberg, 1979), I argue that user and intermediary firms are likely to successfully create novel innovation in high technology industries. However, this impact dampens as industries evolve. Below, I provide three main reasons for my arguments.

First, the process of innovation generation consists of a path from technological invention to commercialized innovation. There is a fundamental critique of the technology-push perspective, which ignores this path from invention to innovation (Nemet, 2009). This view disregards economic conditions and applications, which impact successful innovation commercialization (Nemet, 2009; Kline et al., 1986). Also, the emphasis on technology-push arguments heavily relies on the uni-directionality of innovation (which emphasizes the role of technology producers and unidirectional path from suppliers of technology to users of technology), while ignoring the importance of interaction and feedback in the process of knowledge and innovation generation (Freeman & Louca, 2001; Kline et al., 1986; Nemet, 2009). Often, successful commercialization of innovation heavily relies on complementarity, cumulativeness, and networks of many actors in the industry. This is particularly important in commercialization of novel ideas as overcoming ambiguity and uncertainty in the process of innovation generation is more important for such initiatives. On the other hand, industry-specific attributes are significant in the relative importance of actors on supply and demand in generating knowledge and innovation (Pavitt, 1984). As high technology industries are very fast-paced, I argue that knowledge, interactions, and timely feedback of actors on the demand side of the industry play an important role in the path of generation of especially novel inventions to commercialization of such novel ideas.

Second, the search for knowledge is a very complex process, especially the search for the generation of novel innovation (Fleming & Sorenson, 2001, 2004). Any type of knowledge that can guide the search and reduce its complexity is highly beneficial in the search for novelty. Knowledge of customers and intermediary firms is key to identifying the needs and possible applications of technological and scientific knowledge. I argue that knowledge of actors on the demand side of the industry can work as a map when the search for knowledge is highly complex. Thus, unique knowledge of needs and applications can facilitate the very complex search for novelty by creating useful boundary conditions for the search.

Third, it is likely that the contributions of supply and demand vary over the life cycle of an industry. High technology industries are known to be created following a technological breakthrough and “creative destruction” (Moeen & Agarwal, 2017; Schumpeter, 1942), and their emergence is associated with high levels of uncertainty and ambiguity (Aldrich & Fiol, 1994). Because of higher levels of uncertainty and ambiguity in early stages of industry emergence (Aldrich & Fiol, 1994), it is likely that demand plays a more important role as a map in early stages of industry emergence. For instance, in earlier stages of the small satellite industry, there was a period of “small satellite doldrums” (Jansen, 2011). During this period, customers of technology like AMSAT played a significant role in revitalizing this industry and worked as a map to navigate novel technological advancements. However, as industries converge on a dominant design, it is likely that knowledge of demand plays a less important role in driving knowledge base and novel innovation generation. As a single dominant design wins among rival technologies, firms prefer to exploit current technologies. Thus, knowledge of demand is likely to lose its prominence to work as a map in exploring novel innovation, and be of less value in guiding the search for novel ideas and creating novel innovation.

Hypothesis 1a: *Demand-pull forces are positively associated with the generation of novel innovation.*

Hypothesis 1b: *Demand-pull forces create more novelty in earlier stages of industry emergence than later stages of the industry life cycle.*

Breadth/Diversity of Innovation

Breadth or diversity of innovation is critical in entrepreneurial activities and driving industries (Hunt, 2018). As Hunt (2018: 254) puts it, diversity of innovation shows “distinctive solution sets introduced to the marketplace." I argue that user and intermediary firms are vital contributors to the diversity of ideas and innovation generated, and their contributions heighten as industries evolve. This is for three main reasons. First, knowledge of demand shows a variety of specific needs in the market (Ye, Priem, & Alshwer, 2012). Awareness of latent or societal demand (Hunt, 2018; Schmookler, 1966), and availability of new markets or geographic locations (Griliches, 1957; Vernon, 1966) can increase the diversity of investments in innovation and exploitation of current technologies. As intermediary or user firms are more likely to be aware of needs in the market, they are more likely to benefit from current technologies to address the needs, while it is less likely for firms on the supply side to either exploit current technologies for variety of needs or go far from their current routines to satisfy unmet demands (Gerstner, Konig, Enders, & Hambrick, 2013).

Second, although supply-push and demand-pull are not completely discrete activities (Mowery & Rosenberg, 1979), they are likely to have distinct impacts on the solution sets – "the generalized means through which a need or a want is satisfied" (Hunt, 2018: 252) – that are developed and commercialized. As Hunt (2018: 254) stated, "demand can serve as a generative source of entrepreneurial innovation." Having the knowledge of preferences in the market and feedback on interests in the market and society, more diverse opportunities can be identified, and more competing solution sets can be introduced, represented and commercialized (Hunt, 21018). This knowledge shows how a possible opportunity is not identified, or inaccurately addressed, what the failures are, or how the "boundaries" of the solutions are set. Thus, with more knowledge of demand, it is more likely to have relevant and diverse recognized boundaries to identify an opportunity and respond to it. As a result, a broader set of ideas can be pursued, and more diverse responses to opportunities can be developed.

Third, as industries evolve and technologies converge on a dominant design, firms often try to exploit current knowledge and technologies (Suarez & Utterback, 1995). If firms have knowledge of market demands and changes in the market needs, they are more likely to identify opportunities and generate distinct solution sets based on their current technological domain to address unmet needs. As Rosenberg (1969) argued, demand guides firms to solve problems in the market. The knowledge of demand is likely to be more important as firms try to exploit current technologies within existing innovation processes when industries move toward maturity. For instance, there are many changes and new needs in the small satellite industry as the industry has evolved. Especially with new techniques in data analytics and advances in using big data, many firms entered the industry to use satellite data for a variety of applications. Analyzing big data from satellites provides very high profit margins and attracts many entrants to the industry (Song, 2017). For example, there are firms using image data of satellites for stock market prediction (by calculating the number of cars parked in the parking lots of stores), scientific research and development, earth observations, weather prediction, oil price prediction, etc.

Hypothesis 2a: *Demand-pull forces create more breadth of innovation than supply-push forces.*

Hypothesis 2b: *Demand-pull forces create greater breadth in later stages of industry life cycle than earlier stages of industry emergence.*

Coherence of Innovation

As industries emerge, they are associated with high levels of uncertainty and ambiguity (Aldrich & Fiol, 1994). Creating the convergence, and some level of agreement is necessary for commercialization of products, and driving industries to move to the maturity stage (Suarez et al., 2015). As industries emerge, firms face many technological choices, high levels of uncertainty, and convolution (Eggers, 2014; Townsend, Hunt, McMullen, & Sarasvathy, 2018), and explore many potential options. Eggers (2014: 159) noted the importance of different paths that firms take to transition from old technology to new technologies, or "from one uncertain and speculative variant to another as they receive feedback about the efficacy of their choices." Creation of dominant design and a coherent understanding of technologies makes firms agree and converge on a design and technology, dampens uncertainty (Kretschmer, 2008), and has long term implications on how firms commercialize their products. Also, firms need to develop the knowledge base required to create a coherent understanding of technologies and provide the setting to commercialize the winning technology (Cohen & Levinthal, 1990). Examination of which actors with unique knowledge bases in the industry have the most influence in creating convergence and coherence sheds light on understanding important sources of knowledge to create convergence and overcome uncertainties in industries. I theorize the role of different actors and how their unique knowledge contributes to the creation of convergence. Eggers (2014, 160) argues, "The difficulty in navigating the uncertainty of an emerging new technological space before the establishment of the dominant design is an important subject." As actors who are on the demand side of the industry, have different sets of resources, competences, and knowledge, they are likely to be different from suppliers of technology in creating coherence. I argue that customers are more likely to create coherence in high technology industries, but their impact dampens as industries evolve. My argument is based on the following three tenets.

First, unique knowledge of users and customers helps firms understand problems in new product developments, and bottlenecks in advancing technologies and designs. Also, firms with this knowledge have accumulated experience and capability in applied technologies (Baba et al., 2009). Actors on the demand side of the industry are more likely to have a deeper understanding of the most useful designs and technologies that work for customers. Thus, they are likely to be equipped with a type of knowledge that helps drive the industry toward the appropriate design and technology for users with the potential to be commercialized.

Second, fast-paced high-tech industries are characterized by circumstances in which customers are more likely to actively act on the problems identified and offer appropriate solution sets. This has been apparent in emerging high-tech industries, such as 3D printing that requires high levels of interaction with customers who need customized applications of technologies developed (Kyriakou, Nickerson, & Sabnis, 2017). The interactive process of learning problems and solutions gives customers the knowledge, skills, and capabilities for the creation of a coherent understanding of which technologies can best be used in the long run, as well as insights on how these technologies can best be used. Thus, I argue that knowledge generation efforts of firms that have the unique knowledge of demand are more likely to lead to the creation of the coherent understanding of what works best in the industry.

Third, although advances in science and technology are important contributors to generating knowledge and driving innovation, demand is a more important indicator of invention commercialization (Nemet, 2009). There is a widely-accepted path from basic science to applied technological development to commercialized products (Hunt, 2018). Because of the inherent uncertainty in all stages of the innovation process (Fleming & Sorenson, 2001, 2004), successful commercialization of products is attributable to both addressing uncertainty in the knowledge generation and to demand in the market. Since earlier stages of industry emergence are associated with more uncertainty and ambiguity than later stages of the industry life cycle (Aldrich & Fiol, 1994), contribution of demand to overcoming uncertainties is more prominent in earlier stages.

Prior to the emergence of dominant design, when uncertainties are not resolved, it is likely that firms get trapped in the processes, routines, and knowledge base that could potentially work as a source of inertia (Nelson & Winter, 1982), rather than developing a knowledge base that drives the technological advancements leading to convergence. If firms have the unique knowledge of needs, they are more likely to create a knowledge base (Cohen & Levinthal, 1990) that helps them move along the technological trajectory that addresses needs and leads to convergence. Moving along the technological trajectory that creates and leads to a coherent understanding of the industry, is vital in early stages of industry emergence because of firms' struggle to transform the knowledge they possess to commercialized products, especially if they suffer from competence traps (Leonard-Barton, 1992), and switching cost from technologies other than dominant design to dominant design. Firms may not lack the required technological knowledge, but they need market knowledge to develop products through useful processes, especially in earlier stages of industry emergence; this is because firms are more successful in accumulating knowledge based on their current knowledge base (Cohen & Levinthal, 1990), and they move along a trajectory within their knowledge domain. Taken together, I argue

Hypothesis 3a. *Demand-pull forces create more coherence of innovation than supply-push forces.*

Hypothesis 3b. *Demand-pull forces create more coherence in earlier stages of industry emergence than later stages of industry life cycle.*

2.4 METHODOLOGICAL APPROACH

Focal Context

I use the emerging high technology context of the small satellite industry to test my hypotheses. The industry emerged with the launch of Sputnik 1 in 1957 (Helvajian & Janson, 2008), and has experienced many key events that have shaped the technological advancements, driven the manufacturing, launch, and use of small satellites, and attracted many firms to enter the industry. The summary of key events in the small satellite industry is shown in Table 2-2. Most notably, the creation of CubeSats (satellites that consist of multiple cubic units) (Deepak & Twiggs, 2012) by university professors (Bob Twigg from Stanford University and Jordi Puig-Stuart from CalPoly) created the dominant design of the industry in 1999. This emerging high technology context has experienced a large surge in launches and operating satellites since 2012. The number of small satellites launched between 2000 and 2012 remained almost the same (between 40 and 60), with a surge to around 120 in 2012 and a further increase to 160 in 2015. Also, commercial use of satellites has increased tremendously with an enhanced number of new entrants who try to commercialize their space products. In 2016, the revenue of the satellite industry was $260.5 billion. Main operational functions of satellites are commercial communications (35%), earth observation (19%), government communication (14%), R&D (12%), and navigation (7%) (Satellite Industry Association report, 2017).

[Insert Table 2-2 about here]

Satellites in the small satellite industry are categorized based on their weight, where small satellites are known to be between one hundred kilogram to five hundred kilograms, microsatellites between 10 kilograms and 100 kilograms, nanosatellites between one and 10 kilograms, and picosatellites between 0.1 kilograms and one kilogram (Song, 2017). There are multiple actors in the industry that act as suppliers and users of technology. First, there are numerous segments on the supply side of the industry: there are suppliers of components that are used in the development of small satellites, satellite manufacturers, providers of launch vehicles and ground equipment. Second, on the demand side of the industry, there are satellite operators and companies that are end-users of satellite data (Globe NewsWire; Song, 2017). Table 2-3 shows the main actors on the supply and demand side of the industry. Table 2-4 presents examples of firms and their activities on both the supply and demand side of the industry.

[Insert Table 2-3 and Table 2-4 about here]

The small satellite industry provides an ideal context to examine the role of supply and demand in driving the industry for two reasons. First, this industry consists of multiple players on both the supply and demand side with high levels of contribution to the knowledge base and innovation generation of the industry. As seen in Table 2-2, many crucial events in this industry are driven by customers (governmental, academic, or commercial). For instance, one of the most prominent players in the small satellite industry is AMSAT (Radio Amateur Satellite Corporation), who persisted on using small satellites during the “Small Satellite Doldrums” and helped to reverse the downward trend that the industry experienced. After 2012, with the surging interest in using big data and development of data analytic techniques, many firms entered the industry with interesting applications of technologies. As firms developed interesting applications of satellite data, this industry experienced a surge in the number of satellites launched. This suggests that customer demand plays a significant and unique role at different stages of the industry. Second, this industry is very fast-paced and actors are highly interdependent which makes interactions between supply and demand side of the industry important in driving the knowledge base and innovation. Realizing the important role of both customers and suppliers of technology and their unique knowledge base, industry experts started industry-specific conferences such as the Small Satellite Conference. This has enabled technology developers to obtain information on the needs in the market, and actors on the demand side of the industry to understand the bottlenecks in technological developments and the availability of complementary assets.

Data Collection

I use a novel dataset of all the papers that have been presented at the most attended conference of the small satellite industry (i.e., Small Satellite Conference). The first conference was held in 1987. My data spans from 1987 to 2017. It contains all papers through the 30-year period. This conference was a great platform for all actors in the industry to represent their technological achievements and product development attempts. To make sure that this data is a valid source of information, I conducted interviews with industry experts to confirm that the Small Satellite Conference is representative of firms, universities, and research institutes. Industry players consider this conference to be the best platform to represent their technological and new product development endeavors.

Based on the interviews with around 10 industry experts, I confirmed that this conference is closely monitored by industry actors and is discussed in news outlets (e.g., SpaceNews). Since the articles presented in the conference provide the technical and product developments and updates, it is a great source of how multiple players in the industry contribute to knowledge base and innovation generation in the industry. So, using this database provides an advantage in examining the role of actors from the supply and demand sides in driving the industry. While many studies have used the data of patents to capture innovation (e.g., Adams et al., 2013), this approach is problematic for this study. This is because many firms that are active in this industry are small firms or entrepreneurial ventures that do not often patent their technologies, which was verified by the interviews conducted with experts in the small satellite industry. Another reason is that the small satellite industry is a very volatile and high-speed industry. As a result, many of the firms do not patent their technologies. However, examining the papers in the conference that represent firms' and research institutes' technological and product developments is a very novel and useful source of data (Kapoor & McGrath, 2014).

Variables

Dependent Variables

Prior works that studied the contribution of supply and demand to innovation have mainly used number of patents (e.g., Adams et al., 2013) of firms on the supply or demand side to account for their innovative contribution to the industry. For obvious reasons, numbers of patents is a crude measure as it assumes all patents have the same value, impact, and quality. Also, in some industries patenting is not the primary strategy to represent innovation because of the very fast pace of the industry. Thus, patents are not useful to study the co-creation of demand and supply.

I draw upon a comprehensive source of archival data that consists of more than 2600 papers presented at the most attended conference of the small satellite industry. This approach helps me to analyze how organizations on the supply and demand side contribute to innovation generation in a high technology industry over time. Analyzing textual data of papers provides a rich source of information and has a high potential to investigate unique aspects of innovation (i.e., coherence, novelty, and breadth). I use topic modeling to thematically analyze a large number of textual documents. Specifically, I use structural topic modeling (STM) (Roberts et al., 2013) to analyze scientific topics in papers. In the next section, I introduce topic modeling and explain its use in measuring dependent variables in this study (breadth, novelty, and coherence of innovation). Then, I provide details on the measurement of independent variables (i.e., the level of involvement of supply and demand actors in the small satellite industry, and industry life cycle).

Topic Modeling

Recently scholars have attempted to apply text mining techniques to address research questions that could not be answered previously using conventional statistical methods (Janasik, Honkela, & Bruun, 2009). Text mining is a set of algorithms to extract useful information from large number of textual documents (Frawley, Piatetsky-Shapiro, & Matheus, 1992). Topic modeling is a text analysis method that is best understood as machine learning algorithms that intend to annotate high volume of documents with thematic information (Blei, Ng, & Jordan, 2003). In the past, it has been used – primarily outside management field – to organize, summarize, and assess the importance of large collections of documents, such as emails, publication abstracts, and newspaper archives (Blei & Lafferty, 2009; Griffiths & Steyvers, 2004; Wei & Croft, 2006); and more recently, it has received much more attention in social sciences to analyze large collection of documents (e.g., Mu¨ller, Junglas, vom Brocke, & Debortoli, 2016).

Topic modeling works as an automatic methodology for content analysis, which can be applied as a complementary method to conventional content analysis techniques. It has several characteristics which makes it an appealing method. First, it uses unsupervised machine learning technique, which facilitates inductive approaches to research by proposing topics automatically. This is in contrast to using pre-defined schemas (Urquhart, 2012). Additionally, in case researchers are focused on specific words, this method can be supplemented with "seed words" to provide a more focused analysis of documents (e.g., Jagarlamudi, Daume´, & Udupa, 2012). Second, it can be applied on very large number of documents which makes it feasible to automatically investigate voluminous corpus of documents. Third, as the algorithm identifies topics, they can further be analyzed through statistical methods such as regression or clustering (Debortoli, Müller, Junglas, & vom Brocke, 2016). Analyzing voluminous corpus of documents to extract underlying concepts and their relationships, topic modeling provides a complementary technique to other research methods. For these reasons, it is a powerful technique to discover the patterns of emergence of scientific and technological topics and their relationships in unstructured textual data of scientific publications.

In topic modeling, co-occurrence of words is important in extracting the meaning and generating topics (DiMaggio, Nag, & Blei, 2013). The underlying logic of topic modeling technique is different from other automated content analysis approaches, as it uses patterns of words in corpus of documents to uncover its meaning, which means that it takes a relational approach to words meaning. This is consistent with the idea that meaning does not reside in single words but it emerges in relation between words (DiMaggio et al., 2013). So, in contrast to methods that merely use frequency counts and assign a point to one category, this technique takes a probabilistic approach, meaning that it allows each document to pertain to multiple topics with different degrees of membership. The basic idea on topic modeling is that every textual document shows a combination of latent topics and every topic represents a distribution over the words (words refer to distinct words in the documents), and the importance of each topic—weights of topics—changes from document to document. Thus, documents are presented by a distribution over topics and topics are a probability distribution over words.

I present topic modeling as a new method to discern latent scientific and technological topics and their relationships that are embodied in large-scale collections of scholarly publications. Given that a considerable amount of textual data is unstructured, data may be considered irrelevant when it is not, or it may be incompletely comprehended when it is deemed to be relevant, which results in dubious or fallacious analysis of data. Attempts to analyze large number of documents could also lead to relying on proxies that do not capture the thematic information in scientific and technological topics such as highly used approach of patent classes. These are formidable impediments to address research questions of this paper.

As an antidote to these and other methodological maladies, I utilize topic modeling to analyze the patterns of how words are used in a collection of documents (i.e., papers) in order to extract the latent topics and their relationships based on those patterns. I specifically use structural topic modeling as it benefits from many advantages compared to other algorithms of applying topic modeling, which I will discuss below.

Structural Topic Modeling

There are multiple topic modeling algorithms; widely used ones are hierarchical Dirichlet processes (HDP) (Teh, Jordan, Beal, & Blei, 2005), latent Dirichlet allocation (LDA) (Blei et al., 2003), and structural topic modeling (STM) (Roberts et al., 2013), each with its own advantages and limitations (Blei & Mcauliffe, 2007; Blei & Lafferty, 2009; Hong & Davison, 2010). LDA is one of the mostly used algorithms in the literature to apply topic modeling. It is one of the first and most robust algorithms which was first introduced by Blei et al. (2003) as a technique to extract semantic structures in a body of textual documents. Although the output of standard topic modeling algorithms (e.g., LDA) can further be analyzed to investigate the relationships among topics, there are more efficient techniques that capture topics based on covariates (such as author, date or any other document level characteristic) and report how they are related (Roberts et al., 2013). STM is developed to allow meta-data of documents to be considered when estimating topic distribution over documents (i.e., topic prevalence) and distribution of words over topics (i.e., topic content).

I use STM to capture contribution of demand and supply over time (as meta-data attributes). The introductory primer that follows provides a description and conceptual illustration of STM-based topic modeling. Even without the richer technical details, it will be apparent that STM is both robust and accessible in the analysis of how demand and supply contribute as industries evolve.

Roberts et al. (2013) introduced STM as an extension to previous methods by showing that each topic word distribution and each document topic distribution can vary based on some document level covariates. STM has two benefits over previously used methods applied in topic modeling such as LDA. First, as this algorithm considers some document-level covariates in the process of topic generation, it tends to statistically provide a better fit of the model. Second, it provides a platform to investigate the relationship among topics (i.e., known ex-post), and some known (i.e., known ex-ante) variables. STM is able to analyze the documents and provide these results as coefficient estimates (i.e., known from generalized linear models).

Topic Modeling Application

Consistent with prior works that used topic modeling in other fields (Teh et al., 2005), I use abstracts of papers in the analysis because abstracts generally provide sufficient access to the scientific and technological topics that are embedded in the underlying work. In the next section, I explain how I apply STM to extract scientific and technological topics from the collection of textual documents (abstracts) and conduct further analysis to test the hypotheses.

Preprocessing and Identifying topics

Before implementing topic modeling, textual documents need be preprocessed. This process is very common in text analysis (Feldman & Sanger, 2007). Often, textual data is unstructured; so, it is necessary to create a consistent format to reduce the noise. In order to preprocess data, words that are not critical need to be removed. To accomplish this, a list of stop words are removed from textual documents. Often, common words that are used frequently such as “is”, “was”, “we”, etc. are referred to as stop words. Also, the words that do not appear more than five times in all the documents are removed. This technique makes it possible to focus on informative words.

Preprocessing of data and STM analysis are conducted in R. Applying STM, topics are extracted from the collection. I use statistical metrics that have been developed to identify optimum number of topics, which depends on the quality of identified topics. These metrics are called coherence and exclusivity. Semantic coherence correlates with human judgement and measures the internal coherence of topics and accounts for validity (Mimno, Wallach, Talley, Leenders, & McCallum, 2011). Exclusivity takes similarity among topics into account and it measures distinctness of topics. Since these measures are the function of the number of topics, they are used to identify the optimum number of topics. I use the output of topic modeling to capture my dependent variables as follows.

Breadth: The main specification of STM is that it helps scholars investigate relationships between emerged topics and some document-level (abstract-level) covariates. STM could also be used to explore the relationships between identified topics and covariates, such as interactions or nonlinear relationships. One can interpret coefficient estimates of regression following logics of generalized linear models. To investigate the breadth of the contribution of demand and supply, I use a categorical variable as the main covariate of demand/supply (i.e., whether the document pertains to demand or supply) which has five levels (explained in the next section in more detail). By investigating the relationship between demand/supply and emerged topics, I test how demand/supply contributes to breadth of innovation in industries over time. Breadth of innovation generated by supply/demand is captured by the percentage of positive and significant relationships that supply/demand (document-level covariate) has with the creation of distinct topics (shown as Prevalence in the formula).

I fit the following estimation model to paper abstracts:

$$Prevalence_{ij} \sim B_0 + B_1 * Demand/Supply_i + B_2 * Time_i + B_3 * Demand/Supply_i * Time_i + \varepsilon_i;$$

i represents the ith abstract, and j shows the jth topic. $Prevalence_{ij}$ refers to the matrix showing the results of topic distribution and values. B_0 is the intercept; $Demand/Supply_i$ shows if the abstract i belongs to supply side or demand side (which is a categorical variable with five levels) and B_1 is its coefficient estimates; $Time_i$ is a continuous variable that captures the date of the publication of a paper and B_2 is its coefficient estimates. In addition to examining the main effects, I also model the interaction between $Demand/Supply_i$ and $Time_i$, which is shown by $Demand/Supply_i * Time_i$ for the ith document and its coefficient estimate is captured by B_3.

For each topic, I obtain estimates, p values, and standard errors. This enables the investigation of the association between each topic and the variables incorporated in the model. For instance, the demand/supply estimate reveals how demand or supply contributes to the generation of each topic. The estimate shows that specific kinds of documents (i.e., that relate to supply or demand) are more likely to cover and generate a topic but less likely to cover or generate another. Looking at different time periods (interaction term of B_3), I am able to investigate how demand and supply contribute to the generation of scientific and technological topics over time.

Novelty: Novelty is captured by examining the time of the emergence of the topics. Novel abstracts are identified as ones that generated topics in the first three years of the emergence of the topic (Kaplan & Vakili, 2015). I assume that abstracts are represented by their most important topic (i.e., topic that has the greatest weight on the abstract). For a complete analysis of identifying novel topics, please refer to chapter 3 of this document.

Coherence. This variable captures the level of agreement, convergence, and coherence in the generated topics. This concept is suggested by Mimno et al. (2011). Semantic coherence correlates with human judgement and measures the internal coherence of topics. As noted by Roberts, Stewart, and Tingley (2014: 11) …. "[it] is closely related to pointwise mutual information (Newman, Lau, Grieser, & Baldwin, 2010): it is maximized when the most probable words in a given topic frequently co-occur together." They suggested that it can be captured by the formula below, in which D (m, m′) shows the number of times of co-occurring of words m and m′ in a document. So, considering Z most probable words of topic number k, semantic coherence is as follows:

$$C_k = \sum_{i=2}^{Z} \sum_{j=1}^{i-1} \log\left(\frac{D(m_i, m_j) + 1}{D(m_j)}\right)$$

To measure coherence, I use mean centering.

Independent Variables

Level of Involvement of Supply and Demand Actors in the Small Satellite Industry. To identify papers that have been authored by organizations on the supply or demand side of the industry (Adams et al., 2013), multiple sources of data were used. There are heterogeneous players in the small satellite industry (Song & Gnyawali, 2017). There are firms that supply components used in building small satellites. These components include power systems, thermal controls, ground surveillance and communications, and tracking and monitoring (Song & Gnyawali, 2017). Another group of players is firms that use these components to build small satellites. Also, there are firms with launch vehicles and ground equipment. All these firms and research institutes are considered players on the supply side of the small satellite industry. I define demand in this industry, as firms, universities, or research institutes that either operate satellites or use the data of satellites for some application. Thus, demand is defined as both intermediary firms who operate satellites and end-users who use the data of satellites. I included these organizations in the demand side of the industry, because they have a unique knowledge of what is needed in the market, which differentiates them from other players in the industry. To identify the level of involvement of supply and demand actors, I took the following steps.

First, I collected information on the authors of papers and their affiliation. The papers written by any organization active on either side of the industry is considered innovation by demand or supply. All of the firms and research institutes have been hand-coded in terms of supply and demand (Kapoor & McGrath, 2014). To gather information on firms or research institutes that operate satellites or use the data of satellites (i.e., ones on the demand side of the industry), and those that are on the supply side of the industry, multiple sources of data were used. First, I used a database called "*Gunter's Space Page*." This website (https://space.skyrocket.de/) provides the information on all the satellites that have been launched into space, the name of the firms or research institutes that are contractors or operators of the satellite, satellite mission, date of launch, etc. This is the most complete source of data on launched satellites and is used to identify satellite operators.

Second, to identify the firms that use satellite data, all websites of the companies in the database were checked, as these companies are not necessarily operators of satellites and the data might not be provided in *Gunter's Space Page*. If firms use data of satellites for some applications like weather prediction, stock price prediction, etc., they have been categorized as demand. All organizations that are contractors of building satellites, or suppliers of satellite components (based on *Gunter's Space Page* or firms' websites) have been considered organizations on the supply side of the industry. Also, since many of the papers have been coauthored by multiple authors from different firms or research institutions, I developed a measure to identify the level of involvement of supply and demand actors. I used this measure systematically for all papers included in the sample. I used a categorical variable that has five levels and each level shows the level of involvement of supply and demand. The details of how this variable is measured are provided in Table 2-5.

[Insert Table 2-5 about here]

Industry lifecycle. I categorized papers based on the time they were presented at the conference. To incorporate the satellite industry life cycle, I considered two main stages of the small satellite industry (i.e., before the emergence of the dominant design of CubeSats in 1999, and after the emergence of the dominant design). So, this variable is a categorical variable that has two levels: level 1 from 1987 to 1999, and level 2 from 1999 to 2017.

Summary of the variables and measurements are shown in Table 2-6.

[Insert Table 2-6 about here]

2.5 RESULTS

The first step to measure the dependent variables is to apply topic modeling on the abstracts of papers. When applying topic modeling, the number of topics has to be identified. In order to get optimum number of topics using STM, coherence and exclusivity measures were used. I used R package to apply STM on all 2607 abstracts of papers presented at the conference during the 30 year period. After conducting common pre-processing techniques[1], I checked coherence and exclusivity measures for 50, 60, 70, 80, 90, and 100 topics. I followed prior research to test STM using different number of topics (e.g., Schmiedel, Muller, & vom Brocke, 2018). Table 2-7 shows these measures when the number of topics is set to be 50, 60, 70, 80, 90, and 100. As shown in Table 2-7, 60 and 80 topics give the best estimates of coherence and exclusivity. Applying topic modeling with 60 and 80 topics on documents (i.e., abstracts of papers) and examining the content of topics myself, I finalized my analysis with 80 topics. Figure 2-1 shows how topics are correlated which provides an overview of how topics are related to one another. Figure 2-2 shows the quality of topics based on their exclusivity and semantic coherence measures, and Figure 2-3 represents a sample of topics identified and how words constitute topics. Figure 2-4 shows the distribution of documents that reflect the level of involvement of supply and demand (i.e., all supply, mostly supply, balanced supply and demand, mostly demand, and all demand) over time.

[Insert Table 2-7, Figure 2-1, Figure 2-2, Figure 2-3, and Figure 2-4 about here]

Applying STM, I analyzed multiple outputs to test my hypotheses. Hypothesis 1a predicted that demand is likely to have a positive impact on creating novel innovation. After novel topics are identified, the following estimation model is fit. Since novelty is operationalized as a binary variable, I used logistic regression in R to fit this model.

$$Novelty \sim B_0 + B_1 * Demand/Supply + B_2 * Industry\ Lifecycle + B_3 * Demand/Supply * Industry\ Lifecycle + \varepsilon_i;$$

[1] Please refer to chapter 3 for more details.

As shown in Table 2-8 (Model 1), both all supply (β =1.63, p<0.001) and all demand (β =1.69, p<0.001) have positive impacts on creating novelty. However, demand has higher impact on creating novelty than supply, although the difference is not significant as shown in Table 2-8 (Model 3) (β=0.06, P>0.1). In Model 3, category of all supply is set to be the treatment category and estimates show the difference between other categories and all supply category. The results of the logistic regression shows that demand highly increases the probability of creating novel innovation. This supports hypothesis 1a. Results suggest that as the industry moves from the emergence to the maturity stage, probability of having novel innovation decreases (β =-2.12, P<0.01). As it is shown in Figure 2-5, the category of "mostly demand" has higher impact in earlier stages of the industry, and this impact becomes less prominent as industry evolves. Interestingly there is not much difference between "all supply" and "all demand" categories. This result partially supports hypothesis 1b.

[Insert Table 2-8 and Figure 2-5 about here]

The main attribute of STM is that it makes it possible to test the relationship between document (i.e., paper) level covariates and emerged topics. I use this very important attribute of STM to examine the role of supply and demand on innovation generation in industries over time. In order to examine the role of supply and demand in creating breadth of innovation, I used two main document-level covariates. First, I used 'Industry life cycle' as a categorical variable that reflects the time of the publication of a paper. Second, I used a categorical variable that shows the level of supply and demand involvement in writing the paper which has five levels. For every topic, I generated an output showing all the estimates, p values, and standard errors. The positive significant estimate of demand shows that papers written by actors on the demand side are more likely to create the topic (which reflects innovation). Hypothesis 2a predicted that demand is more likely to have a positive impact on creating a broad set of innovative topics. As results show, in 80% percent of topics (i.e., 64 topics), demand (all demand category) had significant positive relationship with the emergence of the topics. However, supply (all supply category) had significant positive relationship with only 36 percent of topics (i.e., 29 topics). Results suggest that demand explains the emergence of a broader set of topics (the highest number of significant positive relationships with topics created); therefore, demand plays the most important role in contributing to the breadth of the topics or innovation generated. This supports Hypothesis 2a. However, the interaction of time and supply-demand is mostly non-significant in the topics emerged. Thus, time is not a significant moderator of how demand contributes to the breadth of innovation. So, Hypothesis 2b is not supported.

Hypothesis 3a predicted that demand is more likely to create coherence of innovation. To test this hypothesis, I ran linear regression having coherence as my dependent variable and fit the following model.

$$Coherence \sim B_0 + B_1 * Demand/Supply + B_2 * Industry\ Lifecycle + B_3 * Demand/Supply * Industry\ Lifecycle + \varepsilon_i;$$

Although, I did not expect supply to have a significant impact on creating coherence, as Table 2-9 shows (Model 1 and Model 2), all supply (category 1) (β =15.81, p<0.001), mostly supply (category 2) (β =32.2, p<0.001), balanced (category 3) (β =13.87, p<0.001) and all demand (category 5) (β =14.92, p<0.001) have positive impacts on creating more coherent topics. Mostly supply has the highest impact on creating coherence, and as it is shown in Table 2-9 (Model 3), its impact is statistically significantly different from all supply (β =16.38, p<0.001). Although all demand does not have the highest impact on creating coherence, the results show that having some level of involvement of demand creates the highest level of coherence. This partially supports Hypothesis 3a. Hypothesis 3b suggested that demand creates more coherence in the early stages of industry emergence rather than later stages. As it can be seen in Figure 2-6, impact of "mostly supply" category increases over time, whereas the impact of the group "mostly demand" decreases as industry moves from the emergence stage to the maturity stage. This partially supports hypothesis 3b, which predicted that demand plays a more important role in earlier stages of the industry emergence. The summary of hypotheses and findings is shown in Table 2-10.

[Insert Table 2-9, Table 2-10, and Figure 2-6 about here]

2.6 DISCUSSION

In addressing the gap on how and to what extent demand and supply sides of industries contribute to innovation generation and selection as industries emerge and evolve, I have examined breadth and novelty (as aspects of innovation generation) and coherence of innovation (as an aspect of innovation selection) that each side creates over the industry life cycle. Given that innovation – as the main driver of industries – is related to the activities of many actors, including firms, research institutes, and universities on either the supply or demand-side, this paper provides a rich understanding of the contribution of each side to industry emergence and evolution. This paper illustrates how actors on both the supply and demand-side make unique contributions to technological progress, and how they become the locus of innovation based on the distinct aspects of their contributions. In doing so, this study unpacks the nuances that underlie innovation generation and selection, and shows how multiple actors play distinctive and complementary roles in co-creating innovation. This study shifts attention from suppliers' innovation creation to unique aspects of supply and demand innovation co-creation over the industry life cycle.

I chose the small satellite industry as the high technology emerging context. This industry has many players that act as suppliers, customers, or intermediary firms. Because this industry is very high paced, and there is high interaction among multiple players, it is a great context to examine how customers and users contribute to innovation. I used a comprehensive dataset of small satellite conference proceedings that span from 1987 to 2017, which contain 2607 papers published since the emergence of small satellites. Since the small satellite industry emerged, it has witnessed high technological progress that is driven by both suppliers, customers, and end-users. This data provides a rich and comprehensive setting to examine unique aspects of the contributions of customers and suppliers of technologies.

To understand how each side contributes to innovation generation and selection, and consequently, emergence and evolution of industries, examining breadth, novelty, and coherence of innovation is of great importance. Breadth of innovation shows varied solution sets to address problems (Hunt, 2018). This study illustrates that customers play an important role in generating broad solution sets. Novelty of innovation is the main driver of change in technological and scientific innovations and creates economic and social value (Kaplan & Vakili, 2015; Kuhn, 1970; Phene et al., 2006). Prior research on novel innovation has mainly taken the supply-side perspective outside the scope of the industry evolution literature by examining the role of knowledge recombination (Kaplan &Vakili, 2015), founders and CEOs (Tzabbar & Margolis, 2017), R&D teams (Tzabbar & Vestal, 2015), and technological capabilities (Conti et al., 2013) in generating novelty. This study shifts the attention from the role of suppliers to that of users in creating novelty. Coherence creates a convergence and agreement in design and technology, and sets the base for product commercialization (Eggers, 2012, 2014). As industries emerge, they are associated with high levels of uncertainty and ambiguity (Aldrich & Fiol, 1994). Thus, firms attempt to increase their absorptive capacity (Cohen & Levinthal, 1990), create new knowledge (Kapoor & Adner, 2007), and compete for creating technological convergence and dominant design (Eggers, 2012, 2014). There are many scholarly works that aim to explain how technologies and designs converge (Furr & Kapoor, 2018). However, this research stream has mainly focused on suppliers and providers of technology (e.g., Eggers, 2012, 2014; Furr & Kapoor, 2018). This study shifts the attention to the role of customers and suggests that they play a vital role in creating a coherent understanding of the industry.

Results of the study suggest that it is not only supply that drives innovation in high technology industries but also end-users and intermediary user firms play an essential role in emerging and evolving industries. Unlike prior research that focused on suppliers as the main drivers of novelty (Baba et al., 2009), the results of this paper suggest that both supply and demand play important roles in generating novel innovation. Additionally, the results suggest that in earlier stages of industry, demand plays a more prominent role in creating novelty. Also, this study suggests that demand plays a more substantial role in creating breadth. This suggests that customers have unique skills that are needed in the process of knowledge generation, and developing interactive learning mechanisms with customers are useful in generating wider set of innovative solutions. As the results indicate, coherence requires some level of demand involvement. Results suggest that supply and demand co-create coherent understanding, and help players within the industry make sense of the technological advancements that are the most desirable for customers.

Contribution

This study makes three important contributions. First, it contributes to the literature on industry emergence and evolution by theorizing on the role of supply and demand in innovation. Previous research on industry emergence and evolution has mainly examined the role of technology push by looking at technological breakthroughs, competing technologies, and resources of firms, and their role in driving industries (e.g., Agarwal et al., 2004; Furr & Kapoor, 2018; Moeen, 2017; Moeen & Agarwal, 2017). However, there is little scholarly work on how customers and end-users contribute to innovation generation and selection. Addressing this gap is important because innovation is the lifeblood of driving industries, and it is the result of knowledge exchange and diffusion among multiple players (Adams et al., 2013) on both demand and supply side of the industry. Focusing on technological push hinders our understanding of nuances of innovation generation and selection as industries emerge. Addressing this gap sheds light on how and to what extent multiple actors in the industry contribute to knowledge creation, innovation, and industry emergence and evolution. Empirical results suggest that demand is an important driver of how industries emerge and evolve.

Second, this study contributes to the literature on the demand-side perspective, by showing how – in terms of novelty, breadth, and coherence of innovation – customers contribute to innovation generation and selection. Previous studies have mainly examined the role of customers in terms of the amount of their contribution (e.g., Adams et al., 2013) while ignoring unique aspects of innovation generation and selection over the life cycle of the industry. Despite a few attempts, we do not have a clear understanding of the importance, extent, and type of contribution that customers provide to industries. By addressing this gap, this study sheds light on the importance of customers and how demand and supply co-create innovation. Empirical results suggest that demand makes distinct contributions to each aspect of innovation, which varies over the industry life cycle. Finally, besides theoretical and empirical contributions, this study proposes structural topic modeling (Roberts et al., 2013), as an effective method to study innovation in industries. Emerging industries often lack established sources of data. For instance, as industries emerge, there are many entrepreneurial ventures that enter the industry with very limited available data. Also, prior studies have mainly focused on patent data (e.g., patent classes, patent citations, number of patents), and SIC codes, each of which has its own drawbacks (Aharonson & Schilling, 2016), and acts as really crude measures of innovation (Bernardes & Albuquerque, 2003). This is specifically problematic in high tech industries, which are fast-paced, and there is little patenting. This study shows how scholars can benefit from unique and rich data sources that are less often used, such as a large number of documents in the form of text. I demonstrate how researchers can benefit from up to date techniques, and develop unique applications of these methods to answer questions that require analysis of big data.

Implications for Future Research

This study provides three main opportunities for future research. First, future research could conceptually distinguish among multiple actors in the industry. Different actors, such as research institutes, established firms, and entrepreneurial ventures, contribute to the emergence and evolution of industries (Lechevalier et al., 2014; Moeen & Agarwal, 2017). Each of these actors is conceptually different since each has its unique institutional setting, knowledge base and capabilities (McKendrick, Jaffee, Carroll, & Khessina, 2003; Sauermann & Stephan, 2013; York & Lenox, 2014). Although I did not differentiate among these actors, more detailed categorization of actors on demand would add more nuance to how demand contributes to innovation generation and selection. It would also be interesting to examine their contribution throughout the industry life cycle.

Second, research on the demand-side perspective has complemented the research that merely focuses on technology push drivers of innovation. However, little differentiation has been put between consumers (as end-users), and customers (as intermediary firms) (Priem et al., 2012). Similar to previous research, I did not conceptually differentiate between end-users and intermediary firms and how they contribute to innovation generation over the life cycle of the industry. Future researchers could conceptually develop and empirically examine the unique roles of consumers and customers in innovation generation and selection. Conceptually distinguishing between users and customers could bring a more comprehensive understanding of how demand drives innovation.

Third, this study introduces the use of novel datasets and analysis of textual documents that represent innovative activities in industries. Future scholars can use other sources in addition to papers, such as textual documents of patents, to have a more comprehensive understanding of innovative activities in industries. Also, text analysis algorithms provide an appropriate technique for industry evolution scholars. Using up to date techniques and novel datasets is especially important to examine industries in earlier stages because there are often many data limitations that restrict the researchers' ability to study industry emergence. Thus, this study shows fruitful future directions of research to scholars in the fields of innovation, strategic management, and entrepreneurship.

Implications for Practice

This paper has important implications for practitioners. The findings of the paper suggest that knowledge of needs in the market is a vital predictor of commercializing novel innovation. These results are consistent with the findings of Hunt (2018) and Hunt and Ortiz-Hunt (2018) that showed latent societal demand is crucial to the development of scientific ideas. Also, the findings suggest that knowledge of demand creates more diverse commercialized innovation. Considering the "high heterogeneity of need" in the market (Franke & von Hippel, 2003), attention to the needs and problems of both entrepreneurs and managers helps to identify a more diverse set of opportunities. Thus, having relations with customers and consumers, and assessing their needs and problems can help managers to better use knowledge of needs in the market to successfully commercialize diverse solution sets. This study also has significant implications for entrants into new industries. It suggests that managers could use knowledge of needs in the market as a supplement to technological knowledge to overcome ambiguity and uncertainty, especially in early stages of industry emergence. This is meaningful because it is often difficult for firms to make transitions from losing to winning technologies (Furr & Kapoor, 2018). Firms are likely to get trapped in the processes, routines, and knowledge base that could be a source of inertia (Nelson & Winter, 1982). Considering the needs of customers instead of merely relying on technological advancement and finding customers for technologies developed, is likely to be worthwhile. Thus, attentiveness to users' needs and interactive learning processes in the exploration process (Di Stefano et al., 2012) might be necessary for firms' survival.

Limitations

This study has some limitations. First, although much caution and effort have been put on categorizing organizations into either the demand or supply side of the industry, it is difficult to capture how much knowledge of demand or supply that each organization has. For instance, some organizations in the small satellite industry might have multiple roles as both producers and users of technology. So, future research could consider settings in which firms have distinguished roles as either users or producers of technology in the industry. Second, I have tried to confirm the validity of using papers presented at the most attended conference of the small satellite industry –

i.e., the Small Satellite Conference – by conducting interviews with industry experts. Despite the effort to confirm the validity of using the data from the conference, I have assumed that this conference is representative of most of the firms in the industry. However, this data might underrepresent some firms or institutes that did not have the chance or incentive to introduce their products or services at the conference.

Conclusion

This paper underscores that users make essential contributions to innovation generation and selection, and consequently emergence and evolution of industries. This study suggests that suppliers and users make unique contributions to different aspects of innovation. Although both suppliers and users are vital contributors to novelty, the users' contribution is more significant in developing diverse solution sets. Also, this paper suggests that how users and suppliers contribute to innovation generation varies over the industry life cycle. This study sheds light on the nuances of the contributions of users and suppliers of technology to innovation generation over the industry life cycle.

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Table 2-1 Literature Review on Industry Evolution

Study	Research Question	Empirical Setting	Key Findings	Emphasis
Huentler et al., 2016	How does product design shape focus of innovation endeavors and industry knowledge?	Wind turbine technology, 1973–2009, patents	Evolution of industries in terms of technological knowledge is not a unidirectional process, but it is influenced by product hierarchies.	Technological knowledge (supply perspective)
Moeen & Agarwal, 2017	How does the knowledge preceding product evolution evolve?	Agricultural biotechnology industry during its incubation period	Knowledge bases of an emerging industry rely on academia, related, and obsolescing industries	Knowledge contexts in emerging industries (supply perspective)
Agarwal & Shah, 2014	How does firm formation with different knowledge sources impact innovation followed?	Synthesis of the current literature	They point out to the knowledge context of firms and how they contribute to industry over the industry life cycle. They highlight the complementary assets of different sources, and how firms founded by people with different backgrounds will pursue different kinds of innovation. Over the lifecycle of industry, founding of some kind of firms (user, academia, etc.) are more favored to provide complementary assets.	Knowledge context of entrepreneurial firms (supply and demand perspectives)
Lechevalier et al. 2014	How do new industries emerge and evolve? What is the role of different kinds of firms in emergence and evolution of industries	Service robot industry/ data on Japanese patent applications	Established large firms trigger industry emergence more than new firms. Collaborations are highly important in industry formation.	Knowledge of different types of firms (supply perspective)

Eggers 2014	How does choosing winning and losing technologies impact firm outcomes before emergence of dominant design?	Data on the evolution of flat panel display industry, 1965-2005	Knowledge generated in the form of losing technology helps firms switch to winning technology	Technological knowledge (supply perspective)
Agarwal et al., 2004	How does knowledge of incumbents impact their spin out performance?	1977-97 data from the disk drive industry	Incumbents' different types of knowledge impact spinout probability and performance.	Technological knowledge (supply perspective)
Sarkar et al., 2006	How does external knowledge of an entrant impact variation in survival patterns?	3,431 firms over 80 years in 33 industries	In aligned knowledge environment (named as technology regime, and intensity) entrants are more likely to survive.	Technological knowledge (supply perspective)
Collombelli 2014	How does regional level industrial sectors emerge and evolve?	15 EU country analysis, patents, 1986–2006 in nanotechnology	Technological knowledge accumulated locally is likely to impact future patterns of technology diversifications.	Technological knowledge (supply perspective)
Eggers 2012	What are knowledge generation implications of investing in losing technologies?	Flat panel display industry, 1964-2003	Investing in winning and losing technologies has different implications on knowledge paths that firms take which have long lasting impacts on their performance.	Technological knowledge (supply perspective)
Sanderson & Simons 2014	How did solid-state lighting (SSL) industry grow from related light emitting diode (LED) industry?	Historical data on SSL industry and LED	They underlined the importance of participation of firms, research institutes and universities. Some researchers greatly pushed the industry in unexpected ways.	Technological knowledge (supply perspective)

Table 2-2 Key Events in the Small Satellite Industry

Year	Key Events*	Details*
1957	• Sputnik 1 successfully launched	• First artificial earth satellite launched by Soviet Union • Novel technologies emerged
1958	• Explorer 1 successfully launched • Vangaurd 1 successfully launched	• Beginning of the U.S. exploration of space
1960	• Foundation of Aerospace Corporation	• Nonprofit organization • One of the main pioneers of developing small satellites, nanosatellites and picosatellites
1960s	• Increase in the small satellite launches	• Launch vehicle capacity increased
1969	• Foundation of AMSAT (Radio Amateur Satellite Corporation)	• Pioneers of building and operating experiential satellites • One of the main players in driving commercialization of satellites
1977-1987	• Decrease in the small satellite launches	• Less interest in launching small satellites as second payloads and preference of launching larger satellites • Small Satellite Doldrums • Not much impact on experimental/educational satellites launched by AMSAT as they wanted to promote low cost launches for educational/engineering purposes
1981	• Successful launch of first modern small satellite	• Successful launch of this satellite did not lead to entries of firms, until customers could develop commercialized applications until after 2010 where the number of firms founded increased tremendously
1987	• Start of Small Satellite Conference by Utah State University • Start of conference held by AIAA (American Institute of Aeronautics and Astronautics) and DARPA (Defense Advanced Research Agency)	• According to industry experts this conference started to bring together experts in the field of small satellites • Importance of the interactions between producers and customers in driving the industry

	• DARPA investing more heavily in small satellites (Lightsats)	
1987-1999	• Surge in investments in small satellites	• Increase in the launch opportunities • Development of more applications of small satellites
1989	• Start of NASA small explorer programs	• Realizing the importance of small satellites and their applications for different missions • Government and customers driving the industry
1990	• Military actors converging on the use of "smallsats"	• DARPA and Air Force became active in small satellite conference focusing on "Responsive Space" operations
1992	• NASA new approach of "Faster, Better, Cheaper (FBC)" • Start of the use of Microsatellites and Nanosatellites at University of Surrey and Surrey Satellite Technology	• Focusing on size of satellites, cost efficiency, and performance
1997	• Starting the use of nanosats at small satellite conference	• Increased attention to nanosats by producers and customers for product commercialization
1999	• Failures in FBC begin and term becomes obsolete • Introduction of CubeSats	• CubeSats were developed by Bob Twiggs and Jordi Puig-Stuart professors of Stanford University and CalPoly • Introducing a standard in the small satellite industry • Increasing the opportunity of launch as second payloads • Showing the importance of the role of customers (universities who operate satellites for different missions) in driving the industry • Convergence and agreement on using CubeSats
2003	• Responsive Space Conference and emphasis on "operationally responsive" launches	• Six CubeSats were launched by Eurocket vehicle as secondary payloads

	• First Launch of CubeSats	
2007	• Nasa starts ElaNa (Educational launch of nanosatellites) program	• Importance of small satellites for educational purposes and increase in academic programs
2008	• NSF CubeSat program starts	• NSF program encouraged the use of small satellites for obtaining data especially for weather applications • Broad applications started to be introduced
2009	• NRO (The U.S. National Reconnaissance Office) colony program starts	• Launching about 50 triple unit CubeSats mainly for weather purposes
2010	• Start of the CubSsat Launch Initiative • Foundation of Planet Lab as an earth imaging company	• Creating free launch opportunities for useful applications of small satellites • Start of the novel applications of small satellites
2011	• First successful launch of ElaNa	• Showing success in proliferation of programs developed at universities
2013	• High increase in nanosatellites launched by companies • High increase in the launch of 3U CubeSats • First successful launch of PhoneSat	• Surge in commercializing products and applications of small satellites • Ongoing support of NASA of novel applications of small satellites
2016	• Surge in launching CubeSats	• 461 CubeSats launched since its introduction
* Key events and details are taken from Song (2017), Hicks and Niederstrasser (2017), Deepark and Twiggs (2012), Helvajian and Janson (2008), Janson (2011), www.spacenews.com and www.nanosats.eu.		

Table 2-3- Examples of Firms on Supply and Demand Side of the Small Satellite Industry

Examples of companies on the supply side of the industry	Examples of companies on the demand side of the industry
• Pumpkin Inc. Producer of CubeSat kits, processor modules, and batteries • Blue Canyon Technologies. Producer of spacecraft buses, systems, and solutions • Ovonic Battery Co., Inc. Supplier of battery electrodes • Seakr Engineering. Designer and manufacturer of avionic systems	• OmniEarth. Satellite operator and analyzer of satellite imagery • Planalytics. Expert in analysis of satellite data for weather prediction • OneWeb. Satellite operator used for communications and high speed internet • Ursa Space Systems. Analyzer of satellite data for energy analytics

Table 2-4- Main Actors in the Small Satellite Industry

Supply side of the industry	Demand side of the industry
• Suppliers of components of small satellites (power systems, tracking and monitoring, ground surveillance, stabilization) • Satellite designers and manufactures • Launch vehicles and ground equipment	• Satellite operators providing variety of information services (e.g., communications, navigation, and geographic) to end users • End users (government, civil, military, commercial, business)

Table 2-5 Measurement of the Level of Involvement of Supply and Demand Actors in the Small Satellite Industry

Categorical Variable	Measurement
1 (All Supply)	Paper is written by authors from organizations that are all from supply side of the industry
2 (Mostly Supply)	Paper is written by authors from organizations that are mostly from supply side of the industry, and fewer organizations from demand side of the industry
3 (Balanced)	Paper is written with a balance of supply and demand in authorship
4 (Mostly Demand)	Paper is written by authors from organizations that are mostly from demand side of the industry, and fewer organizations from supply side of the industry
5 (All Demand)	Paper is written by authors from organizations that are all from demand side of the industry

Table 2-6 Definitions and Measurement of Variables

Variable	Definition	Measure
Novelty of Innovation	Innovation that "introduces a potential new technological trajectory" which is in contrast to incremental innovation which follows existing trajectories (Kaplan & Vakili, 2015: 1436)	Equals 1 if the paper abstract is considered topic originating, 0 otherwise
Breadth of Innovation	Diversity of the unique solution sets introduced to the market (Hunt, 2018)	The percentage of positive significant relationships that supply/demand (document level covariate) has with the creation of distinct topics
Coherence of Innovation	Convergence in the understanding of technologies and agreement on designs (Kretschmer, 2008)	Captured by formula proposed by Roberts et al. (2014) and captures semantic coherence of topics
Industry Lifecycle	Stages of how businesses operate within an industry	Equals 1 if the paper is written before the emergence of dominant design (1999), 2 otherwise
Level of Involvement of Supply and Demand	Involvement of actors on supply and demand side of the industry in innovation	5 categories based on the level of involvement of organizations on either supply or demand (detailed information in Table 2-5)

Table 2-7 Exclusivity and Semantic Coherence of Models

Number of topics	Exclusivity	Semantic Coherence
50	9.578977	-86.60884
60	9.635077	-90.84272
70	9.650128	-92.18219
80	9.669467	-91.60024
90	9.685361	-94.27725
100	9.702451	-96.10423

Table 2-8 Results of Logistic Regression (DV= Novel Innovation)

	Model 1	Model 2	Model 3
All Supply	1.634**** (0.386)	1.634*** (0.386)	
Mostly Supply	16.566 (1199)	17.566 (1978)	14.931 (1199)
Balanced	0.287 (0.763)	0.287 (0.763)	-1.346 (0.855)
Mostly Demand	1.809 (1.343)	17.566 (2284)	0.175 (1.398))
All Demand	1.695**** (0.283)	1.661**** (0.281)	0.061 (0.479)
Industry Lifecycle2	-2.123*** (0.984)	-1.661 (1.038)	-2.123*** (0.984)
All Supply* Industry Lifecycle2			
Mostly Supply * Industry Lifecycle2			
Balanced * Industry Lifecycle			
Mostly Demand * Industry Lifecycle2		-33.47 (4568)	
All Demand * Industry Lifecycle2			
Constant			1.634**** (0.386)
*P<0.1 , **P<0.05, ***P<0.01, ****P<0.001 Standard Errors in parentheses.			

Table 2-9 Results of Linear Regression (DV= Coherence)

	Model 1	Model 2	Model 3
All Supply	15.816**** (1.522)	15.816**** (1.525)	
Mostly Supply	32.201**** (5.327)	32.201**** (5.336)	16.385*** (5.54)
Balanced	13.870*** (4.026)	13.87**** (4.034)	-1.946 (4.304)
Mostly Demand	8.638 (5.47)	10.471* (6.162)	-7.178 (5.678)
All Demand	14.925**** (1.095)	14.866**** (1.101)	-0.891 (1.875)
Industry Lifecycle2	2.789 (4.974)	4.232 (5.449)	2.798 (4.974)
All Supply* Industry Lifecycle2			
Mostly Supply * Industry Lifecycle2			
Balanced * Industry Lifecycle			
Mostly Demand * Industry Lifecycle2		-8.767 (13.475)	
All Demand * Industry Lifecycle2			
Constant			15.816**** (1.522)
*P<0.1 , **P<0.05, ***P<0.01, ****P<0.001 Standard Errors in parentheses.			

Table 2-10 Summary of Hypotheses and Findings

Hypothesis	Finding
Hypothesis 1a: *Demand-pull forces are positively associated with the generation of novel innovation.*	Supported: Both demand and supply are associated with generating novelty.
Hypothesis 1b: *Demand-pull forces create more novelty in earlier stages of industry emergence than later stages of the industry life cycle.*	Partially supported: Results suggest that demand-pull forces create more novelty (novel innovation) in earlier stages of industry emergence than later stages.
Hypothesis 2a: *Demand-pull forces create more breadth of innovation than supply-push forces.*	Supported: Demand creates more breadth than supply.
Hypothesis 2b: *Demand-pull forces create greater breadth in later stages of industry life cycle than earlier stages of industry emergence.*	Not supported
Hypothesis 3a. *Demand-pull forces create more coherence of innovation than supply-push forces.*	Partially supported: Some level of involvement of demand creates highest level of coherence.
Hypothesis 3b. *Demand-pull forces create more coherence in earlier stages of industry emergence than later stages of industry life cycle.*	Partially supported: Results suggest that demand-pull forces create more coherence in earlier stages of industry emergence than later stages.

Figure 2-1 Correlation among Topics

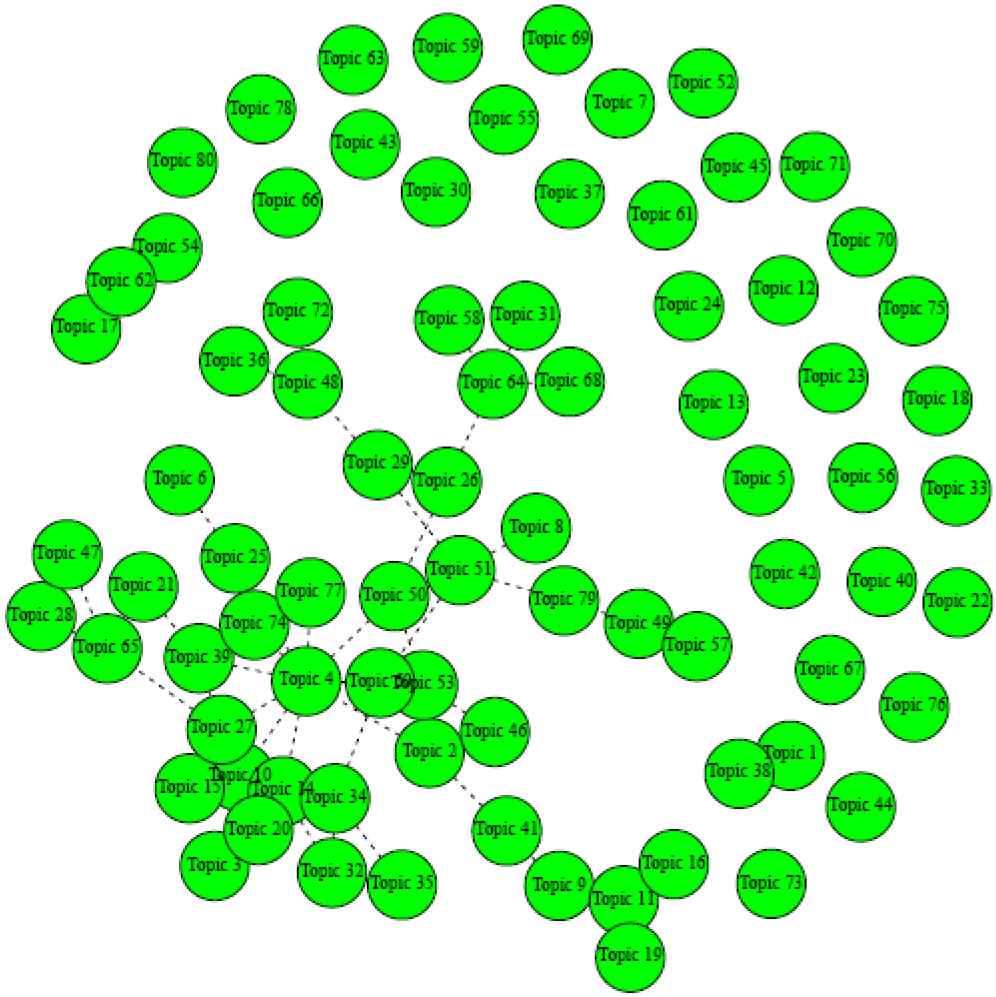


Figure 2-2 Quality of Topics (Coherence and Exclusivity)

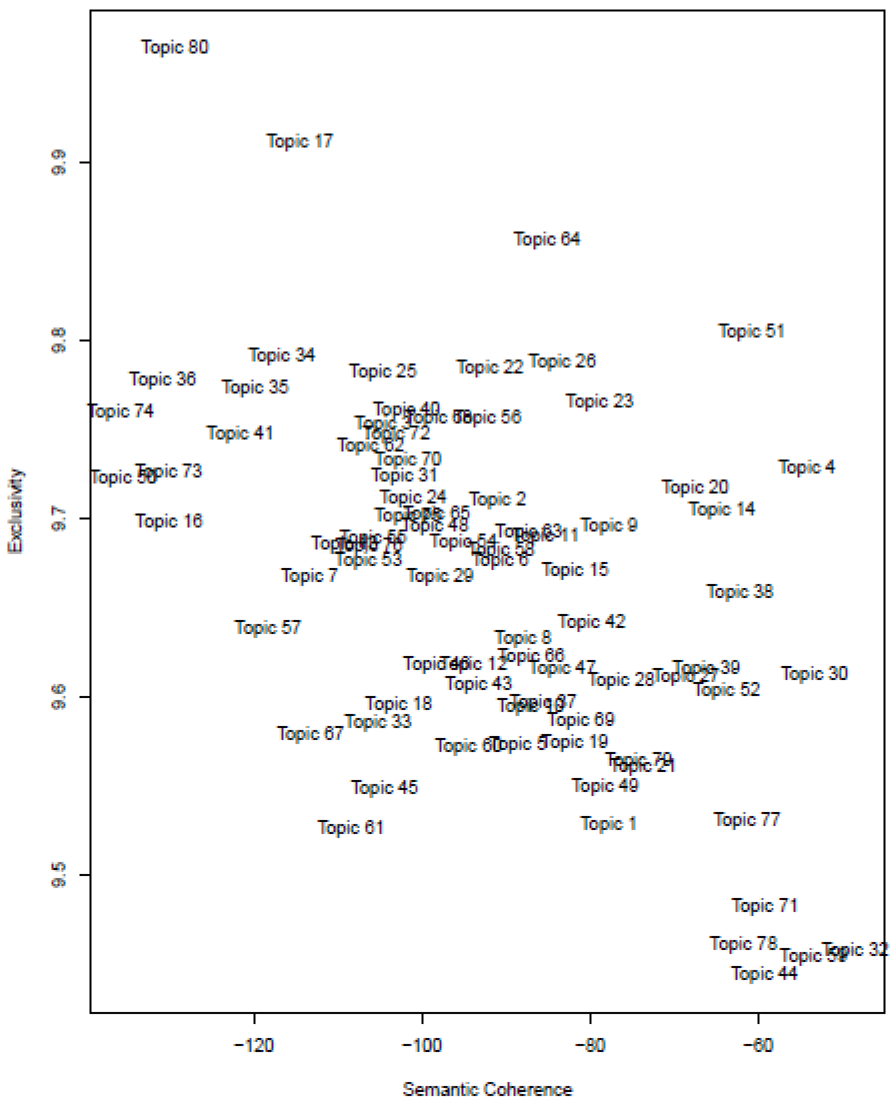
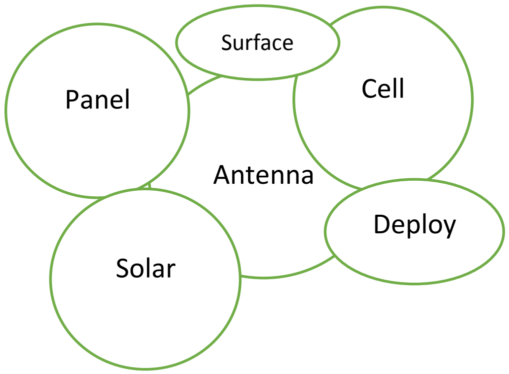


Figure 2-3 Sample of Words in a Topic Emerged

Topic Number 17



Topic Number 55

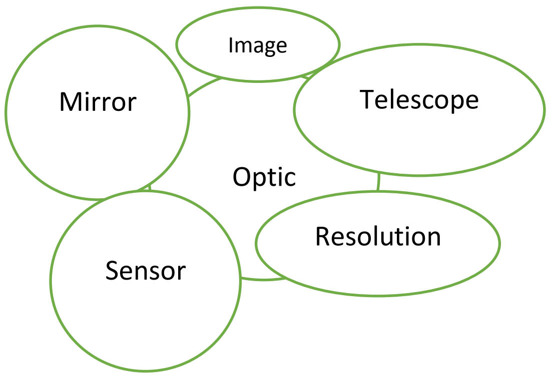


Figure 2-4 Number of Abstracts Based on 5 Categories of the Level of Involvement of Supply and Demand over Time

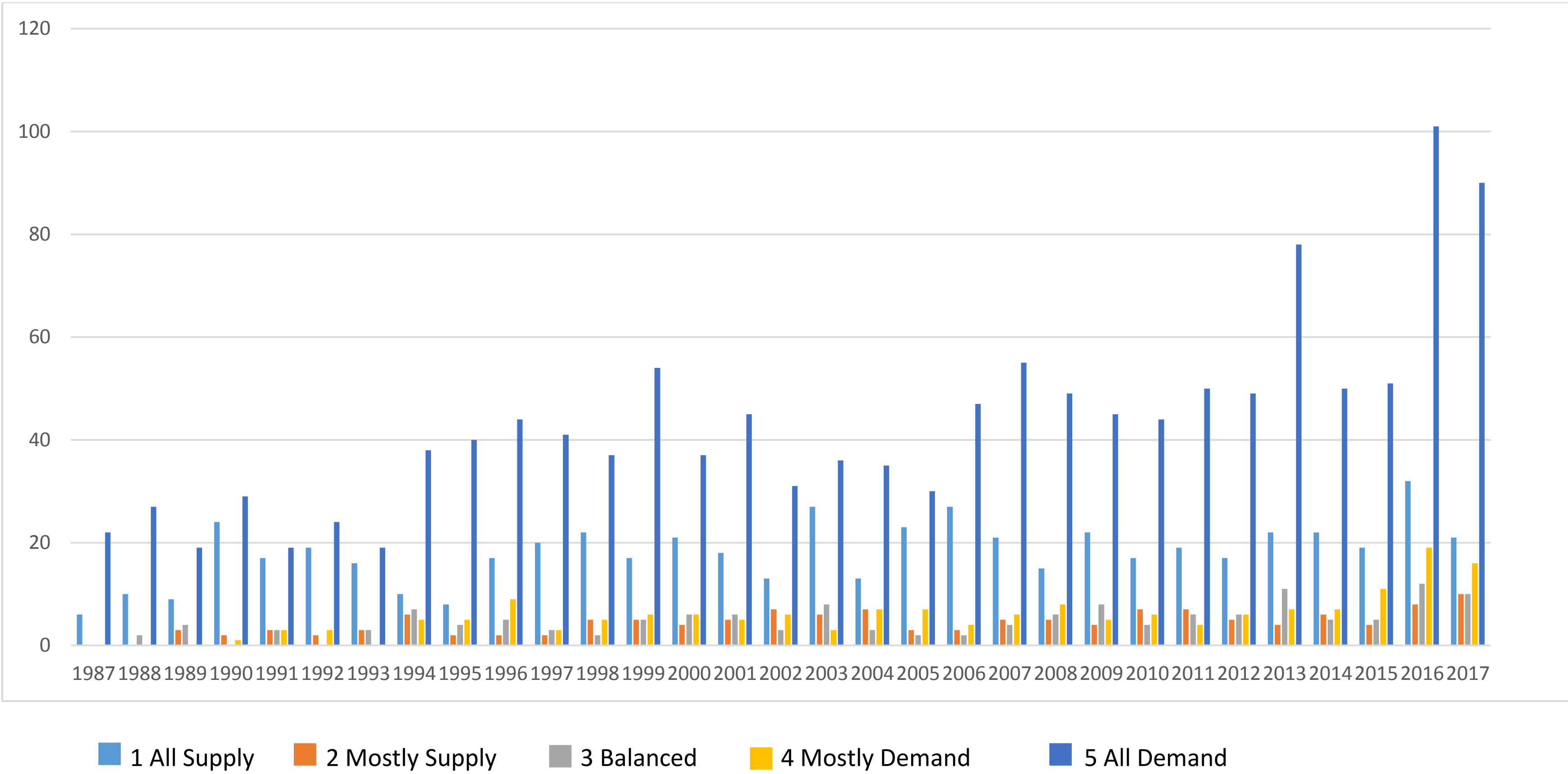


Figure 2-5 Interaction between Different Levels of Involvement of Supply and Demand and Industry Lifecycle (DV= Novelty)

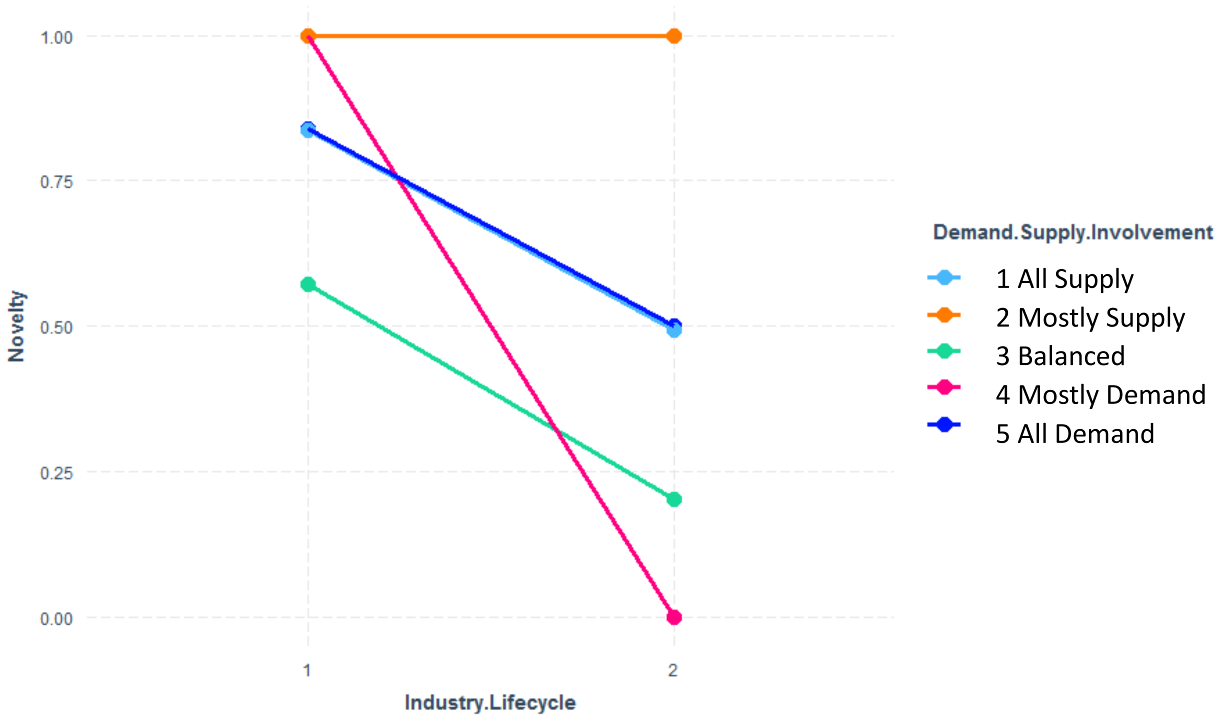
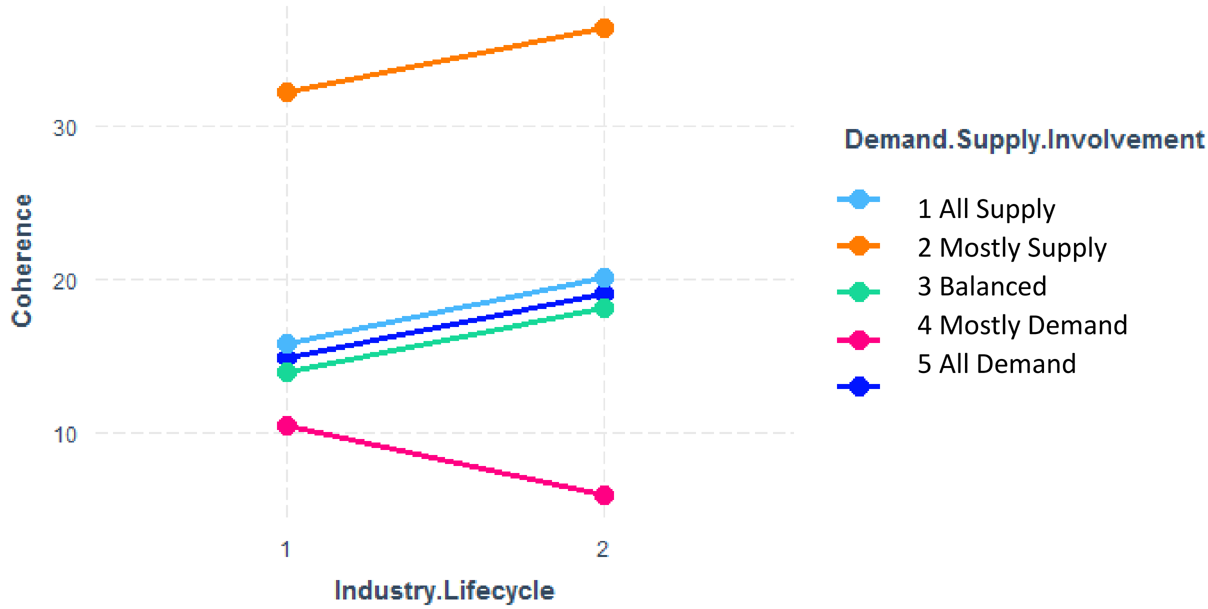


Figure 2-6 Interaction between Different Levels of Involvement of Supply and Demand and Industry Lifecycle (DV= Coherence)



CHAPTER 3: PAPER TWO

NOVEL PURSUITS: THE INTERACTIVE ROLE OF THE CEO'S SCIENTIFIC KNOWLEDGE AND THE SCIENTIST'S BUSINESS KNOWLEDGE [2]

3.1 INTRODUCTION

Novel pursuits, defined as innovations that "introduce potential new technological trajectories" (Kaplan & Vakili, 2015: 1436) are important for a firm's competitive advantage (Eisenhardt & Tabrizi, 1995; McGrath, Tsai, Venkatarman, & MacMillan, 1996). By introducing new technological trajectories, these innovations become primary determinants of change in technological and scientific ideas and contribute to economic value creation (e.g., Phene, Fladmoe-Lindquist, & Marsh, 2006). Firms struggle in novel pursuits, partly due to the misalignment of economic and business goals, on one hand, and scientific goals, on the other hand. Often firms benefit from their current established knowledge and business domains, but such benefits are not necessarily aligned with scientific achievements (Christensen, 1997). Although scholars have pointed out such challenges (e.g., Gibson & Birkinshaw, 2004; He & Wong, 2004), limited research has examined the business-science dynamics, which could potentially facilitate or inhibit novel pursuits. This paper focuses on such business-science tension and investigates the roles of the business and science-related attributes of two of the most important drivers of innovation—scientists and CEOs – inside the firms and examine how they impact the firms' pursuit of novelty.

We build on two literature streams that have developed largely independently in explaining firm innovation: the role of scientists (e.g., Subramanian, Lim, & Soh, 2013) and senior management or CEOs (e.g., Cho & Kim, 2017; Park & Tzabbar, 2016). One stream of literature

[2] This study is developed in collaboration with Dr. Devi R. Gnyawali, and Dr. Manish K. Srivastava.

suggests that the most important drivers of novel innovative pursuits are scientists (e.g., Baba, Shichijo, & Sedita, 2009; Subramanian et al., 2013). This line of research has focused on the scientific or technological knowledge of scientists and has shown that such knowledge is an important driver of innovation (e.g., Baba et al., 2009; Subramanian et al., 2013). Limited research has focused on business knowledge and the experience of scientists and how that would impact a firm's pursuit of novelty. This gap is important because individuals are embedded in all kinds of knowledge that they have obtained, their relationships, and their experiences throughout their careers (e.g., Weng & Lin, 2012); such knowledge and experiences shape their perceptions and behaviors. Specifically, the scientists' business knowledge is likely to impact their cognitive frames and their exploration strategies. Accordingly, we suggest that the business knowledge of scientists has important implications for business-science dynamics in firms, which can then impact the likelihood of pursuits of novel innovations.

On a separate path, scholars have examined the role of the upper echelons on firms' innovative pursuits (Cho & Kim, 2017; Park & Tzabbar, 2016). Although scientists inherently possess the innovative ideas, top managers and particularly CEOs direct and lead the innovative activities of firms (Conti, Gambardella, & Mariani, 2013). However, limited research on CEOs has examined their technological or scientific knowledge. In high technology industries, some CEOs are scientists themselves, have a high passion and inclination toward scientific developments, and pay a large amount of attention to scientific outcomes beyond immediate business outcomes (Cockburn, Henderson, & Stern, 2000). Accordingly, we suggest that the scientific knowledge and experience of CEOs would impact the firms' novel pursuits. The CEOs' scientific background and experience are likely to shape their cognitive frames, which will influence how they notice and interpret scientific or business opportunities, and therefore, their resource allocation for innovation projects. Thus, the CEOs' scientific knowledge and experience would have important implications for business-science dynamics, which can then influence the likelihood of novel innovative pursuits.

We stress the importance of simultaneously examining both: scientists who develop, propose and implement new ideas (e.g., Baba et al., 2009; Subramanian et al., 2013) and CEOs who direct and set the goals of firms (e.g., Cho & Kim, 2017; Park & Tzabbar, 2016). We argue that interactions between CEOs and scientists should have important implications on overcoming the science-business tensions of firms. We suggest that the alignment of time horizons between scientists and CEOs to achieve goals, the level of autonomy that CEOs give scientists to conduct R&D activities and their mutual support are likely to be important in the firms' novel pursuits.

We test our hypotheses using data from an emerging high technology industry of small satellites. We use a novel source of data–NASA grants and papers presented at the Small Satellite Conference–and the novel text analysis technique of topic modeling to discern novel pursuits. Our results show that novel pursuits are high when CEOs have scientific knowledge. Interestingly, the likelihood of novel pursuits is higher when CEOs have scientific knowledge but scientists do not have business knowledge. In contrast with our expectation, the likelihood of novel pursuits is not highest when the CEO has scientific knowledge and the scientist has business knowledge. These findings raise interesting questions that deserve further attention.

This study makes several contributions. First, by theorizing about the role of scientific knowledge for CEOs and business knowledge for scientists, this paper begins to illuminate potential tension between scientific and business knowledge and shows that the effect of such knowledge on novel pursuits is likely to be rather complex and nuanced. Prior research has mainly focused on either the role of scientists (e.g., Baba et al., 2009), or the upper echelons (e.g., Park &

Tzabbar, 2016) on innovation. We bring together these disparate lines of inquiry and delve into the dynamics inside the firms to explore how the CEOs' and scientists' knowledge separately and jointly influence the pursuit of novel innovation. Second, this study contributes to upper echelon literature by examining how the CEOs' scientific knowledge and experience impact the firms' novel pursuits. Focusing on the high technology context, we show how the scientific knowledge of CEOs has important implications for science-business tensions in firms and thus in the pursuit of novel innovation. Third, from a methodological standpoint, we illuminate the possibility of using novel data sources and the usefulness of machine learning techniques to address questions that require big data analysis.

3.2 LITERATURE REVIEW

Knowledge intensive industries and the challenge of innovation

In knowledge-intensive industries, innovation is at the center of the firms' performance and competitive advantage (e.g., McGrath et al., 1996). Although innovation is highly valuable, not all innovations are the same and many are not as valuable as novel innovations (Ahuja & Lampert, 2011). Research has long tried to investigate the determinants of novel innovations, because they are the basis of shifts in science and technology, and create social, firm and individual economic value (Ahuja, Coff, & Lee, 2005; Hall, Jaffe, & Trajtenberg, 2005; Phene et al., 2006). Scholars have taken different lenses to study innovative breakthroughs. Most importantly, there are two main streams of literature that have taken disparate paths to study sources of novel innovation. One stream of literature has examined the upper echelons and their impact on novel innovation (Cho & Kim, 2017; Godart, Maddux, Shipilov, & Galinsky, 2015; Park & Tzabbar, 2016; Tzabbar & Margolis, 2017). Another line of inquiry has focused on knowledge workers and their impact on the pursuit of novel ideas (Subramaniam & Youndt, 2005; Tzabbar & Vestal, 2015). Below, we provide a review of the literature, and the conceptualization of how scientists and the upper echelons, especially CEOs, would impact novel pursuits. Further, we will propose hypotheses and suggest methods to test them.

Literature Review on Scientists and Knowledge Workers

The literature on knowledge workers has examined many scientists' attributes to investigate differential firms' outcomes (Grigotiou & Rothaermel, 2013; Lettl, Rost, & Von Wartburg, 2009; Toh, 2014; Tzabbar, 2009; Tzabbar & Kehoe, 2014). Scholars have shown that the technological distance of scientists (Kotha, George, & Srikanth, 2013; Tzabbar, 2009), scientists' level of knowledge specialization (Toh, 2014), research expertise diversity (Slavova, Fosfuri, & De Castro, 2015), the basic and applied knowledge that scientists possess (Baba et al., 2009; Subramanian et al., 2013), and the variation in experience of scientists in a team (Kotha et al., 2013) are important predictors of the firms' technological repositioning, the scope of technologies firms develop, the likelihood and degree of economic success, technological impact, productivity of research collaborations with alliances and many other performance outcomes.

Among various firm outcomes, the literature on innovation has examined how different aspects of scientists impact novel innovation. Some have examined scientists in their teams – such as the dispersion of scientists (Tzabbar & Vestal, 2015), and their status asymmetry (Tzabbar & Vestal, 2015), while others have emphasized scientists' competencies in terms of the past stock of inventions (Conti et al., 2014), heterogeneity of experience and background (Taylor & Greve, 2006), and the scientists' different institutional experiences in their career trajectories (Agarwal & Ohyama, 2013; Baba et al., 2009; Sauermann & Stephan, 2013; Subramanian et al., 2013).

Among various characteristics of scientists, knowledge and experience they possess are important characteristics when predicting the firms' innovative performance (Kotha et al., 2013).

We argue that the kind of knowledge scientists possess is particularly relevant when predicting novel innovative pursuits that require distinct types of knowledge, expertise, skills, motivation and mentalities. Prior literature has investigated the type of knowledge that scientists possess, mainly in terms of basic and applied knowledge. Basic and applied research are two aspects of knowledge distinguished in the literature, where basic research focuses on fundamental and basic scientific questions and applied research focuses on research that aims to find useful applications in the real world. Baba et al. (2009) studied the firms' collaboration with different kinds of university scientists. Investigating Pasteur scientists (who have above average basic scientific and applied technological knowledge), star scientists (who have above average scientific knowledge) and Edison scientists (who have above average technological knowledge), Baba et al. (2009) showed that collaborations with Pasteur scientists are the most valuable. This is because of the complementarity between the types of knowledge that different parties possess in the collaboration. Similarly, Subramanian et al. (2013) studied the impact of different types of firms' scientists on the firms' outcomes when firms make alliances with universities. They showed that bridging scientists (i.e., scientists active in both basic and applied research) who have more technological knowledge than scientific knowledge work as a complement to the knowledge of universities in R&D collaborations; thus, such scientists have the most positive impact on firm outcomes. These studies highlight the importance of the different types of knowledge of scientists and the differential roles scientists play in the innovative activities of firms. Although the prior literature has attempted to investigate the impact of two kinds of scientists' knowledge on innovation, the studies have remained silent on the implications of scientists' business knowledge on the firms' novel innovation. This is important, since scientists are the main contributors to the novel pursuits of firms (O'Boyle & Aguinis, 2012), and the literature shows that scientists' differences, in terms of their type of knowledge, impact their performance and ultimately firm outcomes (e.g., Subramanian et al., 2013).

Although scientists have been mainly classified based on scientific (i.e., basic research) and technological knowledge (i.e., applied research), researchers have pointed out the importance of other types of knowledge to the firms' outcomes (mainly outside the literature on knowledge workers and with the focus on firm-level knowledge). Hunt (2018) suggested that science falls into three categories of pure, applied and commercialized science. Sauermann and Stephan (2013) categorized science into three categories of basic, applied, and developmental research, where the latter refers to "using knowledge gained from research for the production of materials, devices." (p. 895). The market and knowledge of users' demand have also been emphasized for the innovative activities of firms (e.g., Roy & Sarkar, 2016; Zhou & Li, 2012). Thus, research suggests that besides scientific and technological knowledge, other aspects of knowledge should be important when examining firm innovation activities; however, scholars have mainly examined scientists' scientific and technological knowledge. Implicit in this stream of research is the assumption that scientists lack any knowledge type other than scientific or technological knowledge. A summary of the literature on different types of knowledge that impact firms' outcomes is provided in Table 3-1.

[Insert Table 3-1 about here]

Most importantly, we argue that scientists are different in terms of the knowledge of the business, operations and market side of industry, which is required to generate impactful innovation (Roy & Sarkar, 2016). Teece (1992: 11), emphasizing the knowledge of the needs in the market, argued that manufacturers should have a "deep and enduring relationship" with users to develop new products. Scientists who gather information on what is needed in the market, can better understand what is required and what is likely to have value. They will also be able to gather information on how the competitors' products are working and how they can address problems and needs. Baba et al. (2009: 759), highlighting the importance of the needs in the market, pointed out that "….However, in the field of advanced materials, academic researchers working with firms consider issues such as how to link the new functions made possible through the use of a given material and the development of products, or how to provide end-users with new services". Thus, we argue that, in addition to scientific and technological knowledge, knowledge of the business should be important in the innovative activities of knowledge workers. We suggest that business knowledge is an important knowledge type that relies on commitment, action and involvement in the context of business.

The summary of the review of the literature shows that the different types of knowledge that scientists possess provide different kinds of skills and resources that impact innovative endeavors of firms. Prior literature has investigated scientists' differences of knowledge mostly in terms of scientific and technological knowledge. However, the studies overlooked other kinds of knowledge that scientists are likely to possess over their work experience, and how differences among scientists in terms of business knowledge impact the firms' novel innovative pursuits. We argue that scientists' knowledge of the business should have important implications for the firms' innovation. This is especially important because both scientific/technological knowledge on one hand, and business knowledge on the other hand are important contributors to innovation generation (Baba et al., 2009; Roy & Sarkar, 2016). Since the knowledge of the firm is the accumulation of the knowledge of individuals, it is important to examine how the unique knowledge of individuals with different roles impacts the firms' outcomes.

Although new ideas and innovation endeavors are inherent to individuals, how organizations are managed and R&D activities are organized is likely to impact the direction, productivity and intensity of scientists' efforts (Ahuja, Lampert, Tandon, 2008; Conti et al., 2013). Specifically, the upper echelons direct firm activities toward different goals. The CEOs' perceptions of innovation are likely to impact how firms pursue innovation outcomes (Gerstner, Konig, Enders, & Hambrick, 2013). Thus, in the next section, we provide a literature review of the CEOs' impact on firm outcomes.

Literature Review on Upper Echelons and CEOs

The literature on the upper echelons has examined a wide range of top management teams' and CEOs' attributes that could impact firm outcomes and innovation generation. The most important aspects of CEOs that have been studied in the literature include their personality characteristics, such as narcissism (Gerstner et al., 2013), CEO background, such as social class (Kish-Gephart & Campbell, 2015), CEO demographic similarity with the board of directors (Zhu & Westphal, 2014), CEOs, top management teams, and founders experience, such as career variety or diversity of experience (Crossland, Zyung, Hiller, & Hambrick, 2014; Godart et al., 2015; Tzabbar & Margolis, 2017; Crossland et al., 2014), CEO communication skills (König, Mammen, Luger, Fehn, & Enders, 2018), CEO prestige (Fralich, 2012), career horizon (Cho & Kim, 2017), vision and values (Carton, Murphy, & Clark, 2014), or CEO power (Park & Tzabbr, 2016). The variety of CEO characteristics have been used to explain a set of firm outcomes, such as adopting technological discontinuities (Gerstner et al., 2013), the adaptation to technological change (Eggers & Kaplan, 2009; Kaplan & Tripsas, 2008), strategic dynamism or distinctiveness (Crossland et al., 2014), strategic risk-taking (Kish-Gephart & Campbell, 2015; Fralich, 2012), strategic action (Nadkarni & Barr, 2008), new product developments (Nadkarni & Chen, 2014), and the firms' competitive advantage (Cockburn et al., 2000).

There is a well-studied stream of research that has widely examined CEOs and upper echelons in terms of their managerial cognition, including the temporal focus of CEOs (Nadkarni & Chen, 2014; Nadkarni, Chen, & Chen, 2016), managerial attention (Li, Maggitti, Smith, Tesluk, & Katila, 2013), focus of attention to strategic elements or environmental change (Surroca, Prior, & Giné, 2016; Vergne & Depeyre, 2016), paradoxical and business cognition (Hahn, Preuss, Pinkse, & Figge, 2014; Smith & Tushman, 2005), or the cognitive diversity of the top management team (Kilduff, Angelmar, & Mehra, 2000). According to upper echelons theory, the CEOs' characteristics and background are highly important in the firms' outcomes because "each decision maker brings his or her set of 'givens' to an administrative situation" (Hambrick & Mason, 1984: 194), attributes that shape the CEOs' cognition, along with how they make sense of and process information.

Although prior research has examined a wide variety of CEOs' attributes, studies have remained silent on how the CEO's scientific and technological knowledge and experience impact the firms' outcomes. Although scientific and technological knowledge have been shown to impact innovation, it seems that the literature has assumed that either CEOs lack scientific and technological knowledge or such knowledge of CEOs does not impact firm outcomes. Cockburn et al. (2000) pointed out the importance of the science orientation of CEOs. They noted that there are variations among firms in terms of their inclination toward science-driven innovation activities. Since the CEOs' knowledge type reflects the set of 'givens' they bring to firms (Hambrick & Mason, 1984) and how they process information (Hahn et al., 2014), it should have important implications for the firms' outcomes. Thus, we argue that the scientific knowledge of CEOs is likely to have important implications on firms' innovative outcomes.

3.3 THEORY DEVELOPMENT AND HYPOTHESES

Scientists' Business Knowledge and Experience

Scientists are main contributors to the novel pursuits of firms (O'Boyle & Aguinis, 2012); however, scientists vary in terms of the different types of knowledge they have obtained during their careers. The literature shows that scientists' scientific or technological knowledge highly impacts their performance and ultimately firm outcomes (e.g., Subramanian et al., 2013). We argue that in addition to scientific and technological knowledge, knowledge in the business domain is also important in how scientists pursue novel innovation. Business and market knowledge are necessary for generating impactful innovation (Roy & Sarkar, 2016). Scientists who have gained such knowledge in their careers are likely to impact firm novel innovative pursuits for a couple of reasons.

First, scientists who have business knowledge are more inclined to use new and varied exploration strategies. In industrial settings, it is important to couple scientific knowledge and user demands (Baba et al., 2009). Research suggests that 'good science' does not necessarily lead to good innovation (Gittelman & Kogut, 2003), but firms need to bridge different types of knowledge. Specifically, the knowledge of the business and industry will bridge what is doable and what is needed (Roy & Sarkar, 2016). This understanding is fundamental to resolve business-science tension. Thus, it will help scientists expand search processes beyond existing knowledge domains to satisfy a real need in the market. Since expanding search processes can result in more combinations of knowledge, this will be more likely to generate novel innovation (Laursen & Salter, 2006).

Second, possessing more types of knowledge is likely to impact the cognitive breadth of individuals. Scientists who possess business knowledge in addition to scientific and technological knowledge, who have engaged in different types of research and activities and developed different types of skills, are likely to have more cognitive breadth. Broader cognitive breadth leads to the awareness of a broader range of paradigms and perspectives (Crossland et al., 2014). Thus, these scientists with broad cognitive stocks are usually more capable in bringing new perspectives while tackling problems. Moreover, they are likely to see and notice a wider range of “raw material” to generate novel and creative ideas (Dane, 2010) and to pursue novel innovation generation.

Third, scientists who have business knowledge tend to be different from individuals who do not have business knowledge, in terms of their cognitive flexibility. Having distinct types of knowledge impacts cognitive maps and frames of reference in scientists (Fiske & Taylor, 1991). Varied knowledge and experience can influence cognitive flexibility (Dane, 2010), which would foster creative and novel idea generation (Dane, 2010; Shalley, Zhou, & Oldham, 2004). Research suggests that “conceptual combination and reorganization” fosters creative idea generation (Dane, 2010: 587). Conceptual combination and reorganization constitute the merger of two or more schemas; or they include the reorganization of different aspects of a specific schema (Dane, 2010; Mumford & Gustafson, 1988). To the extent that expert schemas encompass a high level of flexibility, a conceptual combination and reorganization may be facilitated. Since novel innovations require new conceptual combinations, cognitive flexibility is likely to facilitate this.

Thus, scientists who possess business knowledge, along with scientific and technological knowledge, are more likely to use new exploration strategies, and possess more cognitive breadth and cognitive flexibility. This would expand their search processes, bring new perspectives and increase the likelihood of seeing and noticing a wider range of “raw material” and facilitate conceptual combinations and reorganization. These would, therefore, foster novel innovation pursuit.

Hypothesis 1. *Firms with scientists who have business knowledge (in addition to scientific and technological knowledge) are more likely to pursue novelty than firms with scientists who do not have business knowledge.*

Although new ideas and innovation endeavors are inherent to individuals, how organizations are managed and R&D activities are organized is likely to impact the direction, productivity and intensity of the scientists' efforts (Ahuja et al., 2008; Conti et al., 2013). Specifically, CEOs direct firm activities toward different goals. Managers' perceptions of innovation and their cognitive processes are likely to impact how firms pursue innovation outcomes (Gerstner et al., 2013).

CEO Scientific Knowledge and Experience

One of the most important drivers of the strategic directions of firms is the top management team (and most importantly, the CEO, as the most impactful actor in firms) (e.g., Chatterjee & Hambrick, 2011; Hayward, Rindova, & Pollock, 2004); thus, they play a critical role in the pursuit of novel innovations. Insights from the literature on managerial cognition suggest that managers develop ways to overcome limited information processing capacity (Fiske & Taylor, 2008), because they pay particular attention to some stimuli while they ignore others. We argue that there is an opportunity to extend the literature on upper echelons by taking the specific context of high technology and knowledge intensive industries into account. High-tech industries necessitate managers to simultaneously consider highly diverging but connected issues regarding scientific breakthroughs and economic success (Hahn et al., 2014). Thus, firms' top managers "face a great deal of ambiguity in understanding the issues, the implications of these issues for their organizations, and ways to respond to these issues" (Sharma, 2000: 683). To understand how managers make sense of high ambiguity, understanding the cognitive processes of managers or "cognitive filters that admit certain bits of information into the strategizing process while excluding others" could be highly valuable (Porac & Thomas, 2002: 178). Based on cognitive frames or "givens" (March & Simon, 1958), managers make sense of ambiguous cues, which leads them to consider particular strategies (Weick, 1995). These "givens" are often captured by managers' demographic characteristics, or their prior knowledge and experience (e.g., Hambrick, 2007).

Specifically, in high-tech and knowledge intensive industries, managers might have varied levels of inclination toward science and technology because of the inherent taste that they have for scientific and technological research or because of their background, knowledge, and experience as scientists. The managerial focus on the scientific aspects of firms' activities shows the passion and attention of managers to science and technological advancements. Cockburn et al. (2000) pointed out the importance of the scientific orientation of CEOs. They suggested "that differences in 'leadership' or 'vision' across firms had a very significant effect on the decision to adopt the new mode of research" (Cockburn et al., 2000: 1135). They argued that "scientifically trained CEOs will be more likely, all else equal, to adopt the techniques of science- driven drug discovery", although they acknowledged that to empirically capture this insight is challenging.

We argue that CEOs who have scientific knowledge and experience are likely to have different cognitive frames, attend to more scientific cues and are likely to be different from those who attend more to business cues in a couple of ways. First, CEOs with scientific knowledge and experience are likely to attend more to scientific cues, and "admit certain bits of information into the strategizing process" related to science rather than business (Porac & Thomas, 2002: 178). We argue that for CEOs who attend more to scientific goals, novel scientific ideas capture more attention, unlike managers who are more attentive to business goals. Attention to scientific novel pursuits will, therefore, impact managers' decisions and actions. The scientific experience and knowledge of CEOs helps to mitigate the inherent tension between science and business. Thus, they are more receptive to the idea of allocating resources to pursue R&D activities related to novel scientific ideas, and leading and coordinating innovation efforts in that direction. Consequently, this will impact novel innovation generation in firms.

Second, CEOs and top managers can affect attention structure in firms. CEOs and top managers impact others to concentrate on the same 'issues and answers' that they find to be important (Gerstner et al., 2013; Ocasio, 1997). Top managers and most importantly CEOs have power over attention structure in firms and they are able to create "subunits, task forces, and incentives to promote their personally favored agendas" (Gerstner et al., 2013: 265). When managers have scientific knowledge and experience and their attention is directed toward science-related issues and answers, in return, they tend to set up task forces that foster scientific activities. However, if managers attend to more business and economic cues, they are inclined to set up task forces that establish current lines of business, which is in the opposite direction to novel innovation generation. Thus, when managers have scientific knowledge and experience, it would be more probable to generate novel innovation.

Third, managers impact how organizational members should devote their attention (Gerstner et al., 2013). CEOs and managers direct attention patterns by creating a model on how others should spend their time and devote consideration (Gerstner et al., 2013). Thus, if they have scientific knowledge and experience and value science more, they create more legitimacy for the novel scientific framing of organizational members, which will foster more novel innovation pursuits. On the other hand, if they value business-related issues, they will possibly create legitimacy for business and economic efficient activities, which will foster more incremental attempts to drive innovation.

Finally, scientific knowledge and experience can influence noticing and interpreting opportunities. If CEOs have scientific knowledge and experience, and pay more attention to scientific cues, they have a better chance of noticing a wider range of scientific opportunities to change the current trajectories of scientific pursuits, and a narrower range of economic and business issues that could inhibit such attempts. However, managers who attend more to business and economic aspects of their firms are more likely to notice and identify more business opportunities, which could result in more incremental innovation. Moreover, along the threat/opportunity dichotomy, managers who have scientific knowledge and experience and attend to more scientific cues are inclined to interpret scientific driven activities such as R&D investments as opportunities rather than threats. Thus, they are more willing to take risks, which is an inherent prerequisite of novel pursuits (Taylor & Greeve, 2006). In addition, they may be more willing to allocate more resources to R&D activities. However, when managers are focused on business goals, they are more likely to interpret R&D investments and inherent risks as a threat rather than an opportunity (Andersson & Bateman, 2000; Sharma, 2000), which would suppress novel innovation generation.

Taken together, the CEOs' scientific knowledge and experience shape the attention structure in firms and impact how organizational members should devote their time. This also influences noticing and interpreting opportunities. Thus, the CEOs' scientific knowledge and experience would facilitate resource allocation to R&D, support the scientific novel framing of scientists, setting up task forces that foster research activities, noticing a wider range of novel scientific opportunities and interpreting R&D activities as opportunities as opposed to threats. These, accordingly, foster novel innovation pursuits.

Hypothesis 2: *Firms with CEOs who have scientific knowledge and experience are more likely to pursue novel innovation than firms with CEOs who do not have scientific knowledge and experience.*

Intertwined Impact of Scientists and CEOs

Prior research on the impact of scientists and top managers have been developed in two disparate paths. This has resulted in gaps in our understanding of the intertwined impact of upper echelons (especially CEOs) and scientists on the firms' innovative pursuits. This is particularly important because the pursuit of novel ideas requires the ability of scientists to identify and assess the implementation of innovative ideas (Baba et al., 2009; O'Boyle & Aguinis, 2012), and the support of CEOs as they set the direction and goals of the firms (Cho & Kim, 2017; Park & Tzabbar, 2016). The interaction between managers and scientists is especially important in understanding how firms overcome science-business tensions. Most prominently, top managers set the direction of research in firms (Panico, 2009), and they determine the direction of resource allocation to pursue innovative activities (Conti et al., 2013). For instance, firms are different both in terms of providing access and the way they provide access (with or without permission) to leading-edge equipment to scientists (Stern, 2004). Conti et al. (2013), investigating the impact of the prior stock of inventors' inventions on the generation of breakthrough innovation, pointed out the importance of organizational control over R&D projects. Thus, we argue that both scientists and CEOs' attributes should be considered when examining how firms overcome business-science tensions and pursue novel innovation. Interactions among scientists and CEOs are important in several ways.

First, scientists who have business knowledge and CEOs who have scientific knowledge and experience are more likely to have a more efficient knowledge exchange. Top managers have the authority to make decisions concerning resource allocation (Conti et al., 2013; Damanpour & Schneider, 2006; Young, Charns, & Shortell, 2001). Since in industrial settings, scientists, at least to some extent, require the approval of top managers, knowledge exchange is critically important. Strategic disagreements on the projects that scientists are willing to pursue are highly possible in firms with respect to their importance from a business perspective (Klepper & Thompson, 2010; Klepper, 2007). If scientists have business knowledge and CEOs have scientific knowledge and experience, it would facilitate a more efficient exchange of knowledge with CEOs on the research projects. This will increase the chances of greater resource allocations for pursuing the projects.

Second, managers who attend more to scientific cues and scientists who have business knowledge are likely to have more similarities because of their overlapping knowledge and cognitive frames. If managers identify themselves more closely to scientists and vice versa, they are more willing to indicate supportive behavior by virtue of similarity (Tsui, Porter, & Egan, 2002). This can create more trust between managers who attend more to scientific cues and scientists with business knowledge and results in showing more supportive behavior (Tsui et al., 2002). This can, therefore, affect the coordination of innovation activities in firms and facilitates novel pursuits. Moreover, because of similarity, managers are more likely to trust scientists with business knowledge to benefit from autonomy and how to allocate their efforts and resources. Having the autonomy to pursue ideas is highly important in generating novel innovation, since many potentially valuable ideas might never be sought because managers might not find them valuable (Conti et al., 2013).

Finally, managers who have scientific knowledge and experience are more likely to have an acceptable time horizon aligned for payoffs with scientists who have business knowledge. As prior research shows, alignment in an acceptable time horizon for goal achievement is important for effective interaction between different levels in organizations (Heyden, Sidhu, & Volberda, 2018). CEOs with scientific knowledge and experience are usually more accommodating for long-term payoffs. On the other hand, scientists with business knowledge are more likely to understand the business considerations of managers for the acceptable time of payoffs. Given that CEOs decide and articulate conclusions based on their dominant beliefs (Heyden, Reimer, & Van Doorn, 2017), this alignment is highly important. Thus, this alignment can foster scientist and manager interactions, create mutual support and facilitate the coordination of innovative activities. Accordingly, firms that have managers with scientific knowledge and experience, and scientists with business knowledge are more likely to have a greater potential for generating novel innovations.

Taken together, the presence of CEOs with scientific knowledge and experience who attend to more scientific cues and scientists who have business knowledge, will positively impact novel innovation pursuits. This is because of the alignment in their time horizon to achieve such goals, giving more autonomy to scientists, and creating more mutual support, which would facilitate effective interactions and the coordination of innovative activities. Accordingly, this will positively impact novel pursuits.

Hypothesis 3. *CEOs with scientific knowledge and experience will positively moderate the positive impact of scientists who have business knowledge on the firms' novel pursuits.*

How scientists and top managers make a unique and intertwined impact on novel innovation pursuits is shown in Figure 3-1.

[Insert Figure 3-1 about here]

3.4 METHODOLOGICAL APPROACH

Empirical Setting: The Small Satellite Industry

We used the high-tech emerging industry of small satellites for our empirical context. The radical innovation of small satellites has tremendously impacted the traditional satellite industry (Song & Gnyawali, 2017). Small satellites are defined based on their weight (i.e., a maximum of five hundred kilograms (kg)) and have different types. Satellites in this industry are mainly categorized in different groups based on their weight: 1) small satellites, which are typically between one hundred kg and five hundred kg, 2) microsatellites, which are between ten kg and one hundred kg, 3) nanosatellites, which are between one kg and ten kg, 4) picosatellites, which are between 0.1 kg and one kg, and 5) chip-satellites, which are between ten and 1 hundred grams (Song, 2017).

This industry emerged in 1957 with the launch of Sputnik 1, and experienced a decline between 1977 and 1987, with a surge in satellite launches since 2012. Specifically, in the past decade, this industry has experienced a great increase in launches and small satellites operating with varied functions (Satellite Industry Association Report, 2017). CubeSats, which were developed in 1999 by university professors, have become the dominant design of the industry. CubeSats are satellites that consist of a number of cubical units and were developed for scientific and educational purposes. Over time, the application of satellites has changed tremendously. In the earlier stages of the industry life cycle, satellites were mainly used for military purposes, meteorology or reconnaissance (Song, 2017). As the industry has moved to the later stages, many novel applications of satellites have been developed. In the past decade, satellites have been used for many commercial uses, navigation, earth observation, R&D, and scientific purposes (Satellite Industry Association Report, 2017). There are different players in this industry such as diversifying firms, incumbents and startups, where the latter constitutes a large number of firms (Song & Gnyawali, 2017). This industry has attracted many small firms that entered the industry in the past few years. Specifically, with the high profit margins of using satellite data, firms with very novel applications have tried to commercialize their space products.

This industry provides an ideal context for our research for different reasons. First, considerable heterogeneity exists among the scientists who contribute to the industry in terms of their business knowledge and experience. This is mainly because many of scientists in this industry have the experience of working in small firms and have taken different roles, such as roles related to operations or executive roles. Second, CEOs are different in terms of their scientific knowledge and experience. Since this industry facilitates space-related missions, some founders and CEOs are scientists themselves and highly pursue their scientific passions and goals. On the other hand, this industry has started to provide great business opportunities for firms to enter and attract CEOs with only business experience and goals. Third, the entry rate of firms into this industry has increased tremendously in the past decade. As NewSpace Global has reported, there are many companies that are trying to commercialize their space-related products where a large number of them have specifically focused on small satellite technologies. Moreover, many firms in this industry are small and medium-sized, which creates a good context for examining interactions between managers and scientists. Finally, with the very fast pace of the industry, the pursuit of novel innovation generation and novel technologies is more important for the firms' survival. Firms need to pursue novel innovation generation in high technology industries to explore new opportunities. Thus, the tension between the pursuit of scientific advancements and the business and economic goals of firms is more intense in such a setting, which provides a great context to examine how firms overcome the science-business tension. Taken together, this industry provides a great context to examine science-business tension and how the scientists' and CEOs' unique knowledge types impact the pursuit of novelty.

Data Collection and Measures

Since this industry is an emerging industry and most of the firms are not public firms, there are numerous challenges in collecting data. As a first step, to collect the name of firms that are active in the small satellite industry, we used NewSpace Global, which is one of the most credible databases of this industry and provides information on firms that are active in this industry. We interviewed several highly experienced executives from this industry to make sure that this database and the information it provides is reliable and precise. Below, we provide our data sources and measurements of novel pursuits, CEO knowledge and experience, and scientist knowledge and experience.

Dependent Variable

Novel pursuits

We used textual data of NASA grants in NASA SBIR & STTR Program and papers presented at the Small Satellite Conference as main sources of data that capture novel innovative pursuits of firms (Lo, 2015). We argue that novel pursuits can best be captured by examining the content and language of firms' grant applications because innovation ideas are first presented in scientific activities of firms, most importantly in their grant applications. This is because majority of the firms in our sample are small and medium-sized firms that often work with NASA to pursue their novel ideas. Also, based on multiple interviews with industry experts, we confirmed that the Small Satellite Conference is the most important conference of the industry. Most of the firms active in this industry are motivated to present their ideas and new product development attempts at this conference.

In order to capture firms' novel pursuits, we specifically used the text of abstracts of grants awarded in NASA SBIR & STTR Program and papers presented at the Small Satellite Conference. Following Kaplan and Vakili (2015), we use topic modeling as an interesting technique to identify novel pursuits of firms. The reason this method would be an appropriate technique is that this method uses how words co-occur in a set of textual documents (i.e., abstracts) and infer the latent topics in the collection of textual documents together with the weight or probability of every topic on every document. This provides the opportunity to identify the earliest documents (i.e., abstracts) in which the topics have been emerged. To do so, we identified the date that a new topic has emerged in our collection of abstracts of grants and papers. We followed prior research that proposed that the documents (i.e., grants' and papers' abstracts) that are originators of topics are the originators of novel ideas (Kaplan & Vakili, 2015). Following prior research (Kaplan & Vakili, 2015), we set a threshold to identify novelty (in this paper 0.5). We assumed that each document is represented with its most important topic and we identified novelty as documents (i.e., grants' and papers' abstracts) that appeared in the first two years of the topic emergence. A brief introduction to the method used is described in the following section.

Introduction on topic modeling. Topic modeling is a machine learning method which is mainly used on large number of documents to understand and extract latent thematic information (Blei, Ng, & Jordan, 2003). This method has been widely used on different collections of documents, such as patents (Kaplan & Vakili, 2015), or paper abstracts (Griffiths & Steyvers, 2004). The main use of this method is on large volumes of unstructured textual data. In this study, we use this method on a collection of documents – i.e., abstracts extracted from NASA awarded grants – to identify novelty. Topic modeling analyzes the words used in a collection of documents (i.e., abstracts), identifies the patterns, and extracts topics based on the identified patterns. In each topic, the weight of every topic in each document is another output of the algorithm. Topic modeling could be applied with different algorithms such as latent Dirichlet allocation (LDA) (Blei et al., 2003). LDA is the most prominently applied algorithm used in the literature to identify latent topics. The logic behind the applicability of this machine learning technique is that this method is capable to explore large number of textual documents and find the thematic information in them (Blei et al., 2003). This method is specifically suitable to capture novel ideas because the cognitive meaning in textual documents could be captured by the language used in them (Kaplan & Vakili, 2015); and if there are changes in the ideas of textual documents, they could be captured with changes in the language.

In order to identify firms' novel pursuits, following Kaplan and Vakili (2015), we identify documents which are originators of the topics emerged. We do this through identifying the earliest document – i.e., abstract – that contains the emerged topic. We consider these documents as novel pursuits of firms. In this study, following similar applications in the literature (e.g., Kaplan & Vakili, 2015), we use LDA as the computational algorithm to implement topic modeling. A short description of LDA is presented in the following section.

Latent Dirichlet allocation (LDA). Blei et al. (2003) developed LDA as a method to identify semantic structure of a collection of documents. In this method, every document constitutes a number of topics; where topics show distribution on the words, and weights of topics are different in each document. Figure 3-2 illustrates the generative probabilistic model in LDA. Observable variables are the words within documents $wrd_{d,n}$ ($\forall n = 1, \dots, N, \forall d = 1, \dots, D$); however, topics θ_k ($\forall k = 1, \dots, K$), distribution of topics per document β_d ($\forall d = 1, \dots, D$), and topic assignment of words $z_{1:D,1:N}$ are unknown (i.e., unobservable variables). Observable variables are shown by green circles and unobservables are shown by white circles. α and η are the hyperparameters of prior distributions on β_d and θ_k , respectively[3]. The boxes (plates) are representative of the replications, where K shows number of topics, and N shows count of all words (i.e., unique words in abstracts or documents), and D shows the number of all textual documents (in our case abstracts are representative of documents).

[Insert Figure 3-2 about here]

The arrows in Figure 3-2 shows conditional dependencies between variables as follows: $z_{1:D,1:N}$ which refers to per-word topic assignment is dependent on topics distribution on each document β_d, and $wrd_{d,n}$ which refers to the word observed in every document is a variable dependent on $z_{1:D,1:N}$ and the topics θ_k's. With all these conditional dependencies, it would be possible to identify the distribution of both observed and unobservable variables. Thus, LDA uses Bayesian learning to derive unobservable variables calculating the posterior distribution based on the distribution of both unobserved and observed variables.

Inferring the unobservable variables leads to understanding the semantic structure of the documents. In other words, applying LDA, two main outputs are derived; topics θ_k and their importance (i.e., their weight) in the documents β_d. More specifically, each document can be summarized by the topics with the highest weight and every topic is a combination of words that have the largest probability of occurrence[4]. To apply LDA, scholars have to specify the number of

[3] The value of these parameters should be assigned by the user. According to the properties of Dirichlet distribution, these values should always be positive. If the values are greater than 1, we would have an even distribution on words/topics, however, if the values are smaller than 1, we would have a sparse distribution on fewer words/topics.
[4]From LDA process, each document (i.e., abstract) shows a distribution on K topics. Also, every topic shows a distribution on N words. Thus, every topic has a probability of emergence in a document; also every word has a probability of emergence in any topic. We assumed that every document (i.e., abstract) is represented with its highest probability topic, and every topic is represented with top ten words that have the highest probability of appearance.

topics. Following related literature and based on our number of abstracts in our collection of documents (Blei & Lafferty, 2007; Hall, Jurafsky, & Manning, 2008; Kaplan & Vakili, 2015), we limited the number of topics to 65.

Applying LDA. Before applying LDA, similar to other text mining studies, we conducted standard preprocessing techniques to prepare our abstracts for the main analysis (Feldman & Sanger, 2007). Preprocessing is common in text mining as textual documents are typically unstructured and noisy. Preprocessing removes words that are not important in our analysis; thus, we removed a standard list of words–commonly called stop words–such as “is”, “we”, “was’, etc. Also, we removed words that appeared less than five times in the whole collection of our documents. Finally, as a result, we had a collection of documents with the important informative words for the analysis. We conducted LDA analysis and preprocessing in Python. The nltk library (Joakim, 2012) and genism python library (Gensim Python software library) were used for preprocessing analysis and LDA analysis respectively. To conduct LDA, similar to common practices in the literature, we used 0.1 for hyperparameters α and η. An illustrative example of applying topic modeling on abstracts of papers and grants is shown in Figure 3-3.

[Insert Figure 3-3 about here]

Independent Variables

CEO knowledge and experience

We collected all the background information of CEOs of firms in our sample from LinkedIn. Based on CEOs level of education and experience, we operationalized this variable; such that if they had Ph.D. in scientific or technological major or had science related roles (such as chief scientists), we considered this variable to be 1, and 0 otherwise.

Scientist Business Knowledge

We identified scientists based on the information provided by grants and their principal investigators and authors of papers. We used LinkedIn to capture scientists' business knowledge and experience. It was captured based on domain and field of study and their experience. If they had any business related education (e.g., MBA or economics), or functional roles related to business (e.g., operations, marketing roles), this variable was considered as 1, and 0 otherwise.

Control variables

We used a range of variables in order to control for firm-related factors that may influence novel pursuits. We used data provided by NewSpace Global. This database provides rankings (from 0 to 10) in four areas for each firm: technology, capitalization, management team, and market. We used these rankings as well as firm size and position in the market as control variables.

3.5 RESULTS

Our final sample from which we could get complete information of authors (scientists), and CEOs of the firms is as follows. We observed 655 grants that have been awarded by NASA to firms that are active in the small satellite industry. These grants have been awarded to 78 firms, and they have been proposed by 309 scientists. We also observed 180 conference papers that were written by authors from the firms in the sample of firms identified to be active in the small satellite industry. These papers have been written by 134 scientists from 77 firms. This added 60 new firms to the sample of grants, and 122 new scientists, making the total sample size 138 firms, 443 scientists, and 834 documents (grants and papers). Applying topic modeling on the textual abstracts of grants and papers, we identified 161 number of firms' novel pursuits[5]. The definitions

[5] Please refer to data and method section for complete details on how novel pursuits are identified.

and measures of our variables are shown in Table 3-2. Descriptive statistics and correlations are shown in Table 3-3.

[Insert Table 3-2 and Table 3-3 about here]

We used logistic regression to test our hypotheses. The results are shown in Table 3-4.

[Insert Table 3-4 about here]

In Hypothesis 1, we hypothesized that firms with scientists who have business knowledge are more likely to pursue novelty. As it can be seen in Table 3-4, Model 2, this hypothesis is not supported. In Hypothesis 2, we hypothesized that firms with CEOs who have scientific knowledge and experience are more likely to have novel pursuits. As it can be seen in Table 3-4, Model 2, this hypothesis is supported (0.951, $P<0.1$). However, testing Hypothesis 3 revealed some very interesting results. As shown in Figure 3-4, contrary to our expectations the likelihood of novel pursuits is not the highest when the CEO has the scientific knowledge and the scientist has the business knowledge. Our results show that when CEOs have scientific knowledge but scientists do not have business knowledge, the likelihood of novel pursuits is greater than when scientists have business knowledge and CEOs have scientific knowledge, or when scientists have no business knowledge and CEOs have no scientific knowledge.

[Insert Figure 3-4 about here]

Robustness Test

As it can be seen in Table 3-4, coefficient of years (as indicators of time) are mostly high and statistically significant in Model 1, Model 2 and Model 3. In order to account for the effect of time, we ran cox regression analysis (Cox, 1972). This model shows the probability of occurrence of an event, taking the time of the occurrence of the event into account. Results are shown in Table 3-5. As it can be seen the CEOs' scientific knowledge positively impacts the pursuit of novelty (0.949, $P<0.01$). Similar to previous results, scientists' business knowledge does not have a significant impact on firms' novel pursuits. These results confirm the results from logistic regression analysis.

[Insert Table 3-5 about here]

3.6 DISCUSSION

This paper was motivated by a tension between scientific and business knowledge for novel pursuits. While the pursuit of novel innovation requires both business and scientific knowledge, often in an iterative manner, these two bodies of knowledge or their sources are not necessarily compatible. Prior research suggests that scientific goals on one hand and business and economic goals on the other hand can be incompatible (Christensen, 1997) and has pointed out such challenges (e.g., Gibson & Birkinshaw, 2004; He & Wong, 2004). However, limited research has delved into this issue by jointly examining the role of scientists' and executives' knowledge in the firms' pursuit of novel innovation. To address this important issue, we examined the direct and intertwined impacts of the CEOs' scientific knowledge and scientists' business knowledge on novel pursuits.

Prior research has mainly examined the scientists' impact on novel pursuits focusing on their scientific or technological knowledge (e.g., Baba et al., 2009; Subramanian et al., 2013), while ignoring their business knowledge. We challenged the assumption that scientists are valuable only for their scientific knowledge and argued that the scientists' business knowledge is important, especially in studying how firms overcome business-science tensions and pursue novel innovation. This is important because the scientists' prior knowledge and experiences are likely to shape their understanding of current problems and their behavior. We also examined how the CEOs' scientific knowledge and experience impact the firms' novel innovative pursuits. Specifically, in high-tech industries, where CEOs need to simultaneously consider divergent business and scientific goals, they face a high level of ambiguity (Sharma, 2000). Thus, their cognitive processes are highly important in the strategic decisions and directions of firms. We built on the literature for managerial cognition that suggests that managers' backgrounds shape their cognitive frames (e.g., Hambrick & Mason, 1984). As suggested by Hamrick (2007: 335), "demographic characteristics of executive can be used as valid, albeit incomplete and imprecise, proxies of executives' cognitive frames." In high-tech industries, some CEOs are scientists themselves and have a high passion toward the scientific endeavors of firms. We argued that the CEOs scientific knowledge and experience would be important in understanding how firms overcome the business-science challenge in their pursuit of novel innovation.

Although our results were somewhat contrary to our expectation, they provide very interesting insights. First, aligned with our expectation, our results suggest that the CEO's scientific knowledge increases the probability of the firms' novel pursuits. This suggests that the CEOs' prior scientific roles or scientific education impacts how they interpret the innovative attempts of firms and increases the firms' inclination toward novel innovation generation. Second, contrary to our expectation, we did not find a significant impact of the scientists' business knowledge on the firms' innovative pursuits. One possible explanation might be related to the scope of activities of scientists in the firms of our sample. It is possible that the responsibility of choosing the new ideas and products to be developed might be delegated away from scientists to middle managers, or other groups in the firm. Third, in contrast to our expectation, our results showed that when CEOs have scientific knowledge but scientists do not have business knowledge, the likelihood of novel pursuits is greater than when scientists have business knowledge and CEOs have scientific knowledge or when scientists have no business knowledge and CEOs have no scientific knowledge. These results suggest that when the gap in knowledge, cognitive frames and understanding between CEOs and scientists is only filled by the CEOs' scientific knowledge, the probability of the firms' novel pursuits is increased. However, when this gap is filled by both the scientists' business knowledge and the CEOs' scientific knowledge, the probability of having novel pursuits is decreased. Our study while explicating tension between science and business raises some very interesting new questions for future studies.

Contribution

This study makes three important contributions. First, it contributes to the literature on novel innovation by providing new explanations on how firms overcome their business-science tensions to pursue novelty. By bringing together disparate lines of inquiry on the role of scientists and of CEOs, we broaden our understanding of how firms overcome business-science tensions and pursue novel innovation. We examined the intertwined impact of the CEOs' scientific knowledge and experience and the scientists' business knowledge. We theorized about the role of scientific knowledge for CEOs and business knowledge for scientists and illuminated the potential tension between scientific and business knowledge. Empirical results show that the effect of such knowledge on novel pursuits is likely to be rather complex and nuanced.

Second, this study contributes to the upper echelons literature by examining how the CEOs' scientific knowledge and experience impact the firms' novel pursuits. Focusing on a high technology context, we showed how the scientific knowledge of CEOs has important implications on science-business tensions in firms and therefore, in pursuit of novel innovation. Our study highlights when and under what conditions the CEOs' scientific knowledge and experience impact the firms' novel pursuits. Third, our use of topic modeling to uncover and examine novel pursuits by doing a text analysis of grant applications illustrates the value of this approach for future research in similar areas. We believe that future research can use this approach, especially when a large amount of text is needed to be analyzed to identify early topics and themes and how those topics evolve over time.

Directions for Future Research

This study provides three promising directions for future research. First, it opens a new direction for research on novel innovation generation. To generate innovation, firms have to recombine knowledge in novel ways (e.g., Kogut, & Zander, 1992); thus, scholarly works suggest that knowledge is the main contributor to innovative advancements in firms (e.g., Srivastava & Gnyawali, 2011). Although there is a distinction between scientific and technological knowledge, this study did not distinguish between these two types of knowledge. The majority of literature on knowledge-based activities and knowledge organization has made a clear distinction between basic research that focuses on fundamental scientific research, and applied research that focuses on technological applications (Stokes, 1997; Murray & Stern, 2007). The former is referred to as science, and the latter as technology. Distinct forms of knowledge make unique contributions to firm performance (Durand, Bruyaka, & Mangematin, 2008). Specifically, science works as a map for innovation generation in firms (Fleming & Sorenson, 2004) and it plays an important role in developing the absorptive capacity required to be in the network of knowledge and information exchange (Chaves & Moro, 2007). Future studies can further distinguish between the different types of knowledge that individuals possess. For instance, they can distinguish between the scientific or technological knowledge that scientists or CEOs have obtained. Thus, future scholarly works can examine other types of knowledge and how they impact science-business tension in firms and their novel pursuits.

Second, although prior research has pointed out the importance of both scientific and business knowledge (Baba et al., 2009; Roy & Sarkar, 2016) in generating innovation, this study shows that in addition to the type of knowledge, the role of individuals who possess a specific kind of knowledge is important in how firms pursue innovation. Future scholars can further examine how the knowledge possessed by other organizational roles who possess specific kinds of knowledge could impact innovation generation. This is specifically important as it generates insights on how multi-level interactions in firms impact overcoming business-science tension. For instance, future scholars can examine how unique knowledge types held by middle managers or top management teams impact the firms' pursuit of innovation. Moreover, future scholarly works can examine the impact of specific knowledge types held by varied roles in organizations on different types of innovation (e.g., incremental or novel innovation).

Third, this study shows opportunities for future research to examine understudied contexts such as emerging industries that lack established sources of data. In this study, we used data sources that are not often used by prior studies (c.f. Kapoor & McGrath, 2014; Lo, 2015), and analyzed the textual content of scientific documents (Blei et al., 2003). This suggests that future researchers can benefit from underutilized sources of data and find novel applications of more up to date methods to examine new emerging contexts.

Implications for Practice

This study has important implications for managers and practitioners. The results of the study suggest that CEOs who have scientific knowledge play an important role in how firms pursue innovation. This highlights the importance of prior scientific roles and the education of upper echelons, unlike the emphasis that has long been placed on their business and executive roles. This is especially important in knowledge-intensive high technology industries where novel innovation is the main driver of technological change and the firms' success (Kaplan & Vakili, 2015; Phene et al., 2006). Thus, the findings of the study show the value of scientist CEOs and encourage the hiring and retention of CEOs who have this type of knowledge. Second, the study suggests that, especially in small firms, interactions between managers and employees are highly important in how firms pursue innovation. The results of the study show that the knowledge gap between managers and scientists is better filled with the CEOs' knowledge. Findings imply that if the knowledge gap is filled with both scientists' and managers' knowledge, this might result in more conflict on how firms should pursue innovation. This might be caused by the overconfidence of either scientists or CEOs because of their knowledge in both scientific and business domains, and an underestimation of the others' knowledge. In addition, the results suggest that if the knowledge gap is not filled by either scientists or CEOs, firms are unlikely to be successful in generating novel innovation. This shows the negative impacts of ineffective communications between different levels of hierarchy in firms. While the results of the study encourage firms to fill the knowledge gap between managers and scientists, it suggests that firms need to be alert and cautious in how they attempt to fill the knowledge gap.

Limitation

This study benefits from some methodological and design strengths and suffers from some limitations. Here, we point out a few limitations. First, the context of this paper is a high-tech emerging industry. Emerging industries are often associated with limited established data sources. Additionally, not many firms patent in this industry. Thus, unlike prior studies that used patent classes as a main source of data to identify the boundaries of an industry and compile the sample of firms, in this study, we used a data source published by NewSpace Global to identify firms that are active in this industry. Although we have confirmed that NewSpace Global is the most reliable source of data, it might underrepresent some of the firms that are active in this industry. Second, to capture the firms' innovation, we used data from grants (Lo, 2015) and papers (Kapoor & McGrath, 2014). Although prior studies have mainly used the data from patents to measure innovation in many industries (e.g., Kaplan & Vakili, 2015; Phene et al., 2006), we have confirmed that many firms in this industry do not patent for two main reasons. First, this industry is very fast-paced. Second, many firms that are active in this industry are small and do not patent because of the high patenting costs. Although we have confirmed that the Small Satellite Conference and SBIR STTR grants are representative of the firms' innovative pursuits, some firms might not be motivated to present their research and product development ideas at the conference or to attract resources via grant applications. Thus, using these sources of data might underrepresent the firms' innovative activities.

Conclusion

In conclusion, this study has important implications as firms face science-business tension when pursuing novelty, specifically in high technology environments. It shows that CEOs' scientific knowledge is important in high technology industries. Our results suggest that the impact of CEOs' scientific knowledge on novel pursuits is higher when scientists do not have business knowledge rather than when CEOs have scientific knowledge and scientists have business knowledge. This study sheds light on the importance of the knowledge gap between scientists and CEOs and how it should be filled. Our study provides important insights to both practitioners and scholars on how firms overcome science-business tensions in their pursuit of novelty. This study introduces interesting new directions for future scholarly research.

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Figure 3-1 How Scientists and CEOs Independently and Jointly Impact Firms' Novel Pursuits

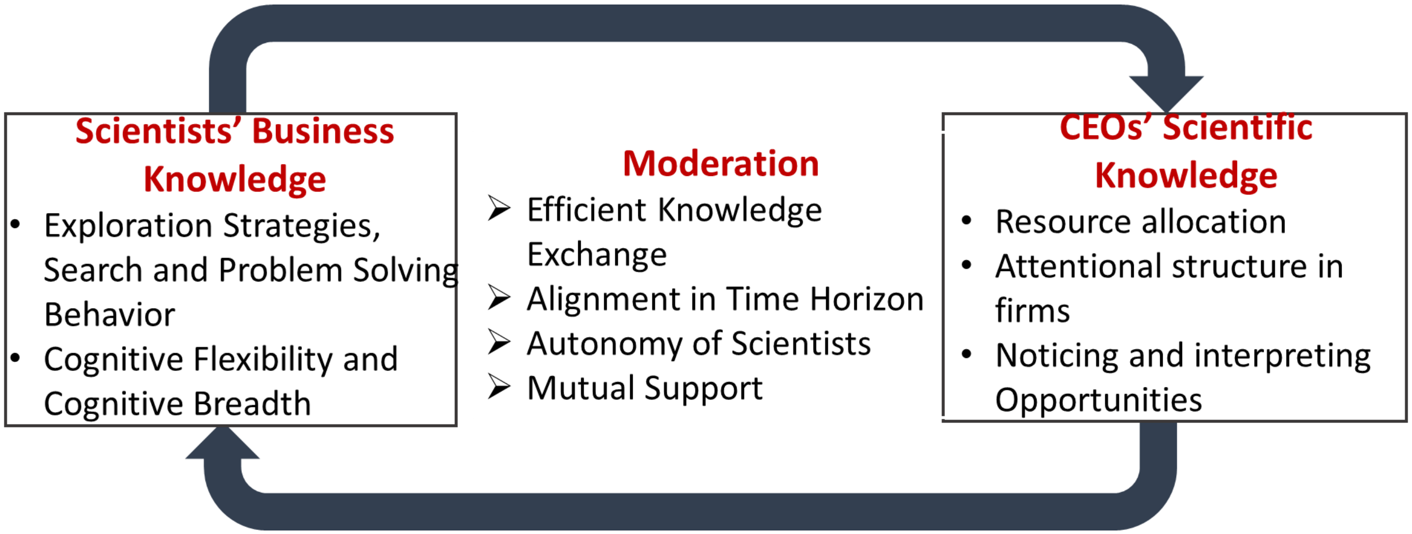

Figure 3-2 LDA-based Topic Modeling (Blei et al., 2003)

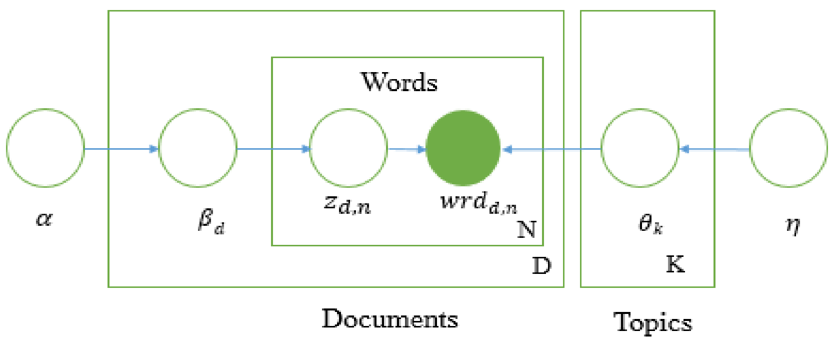

Figure 3-3 Illustrative Example of Applying Topic Modeling

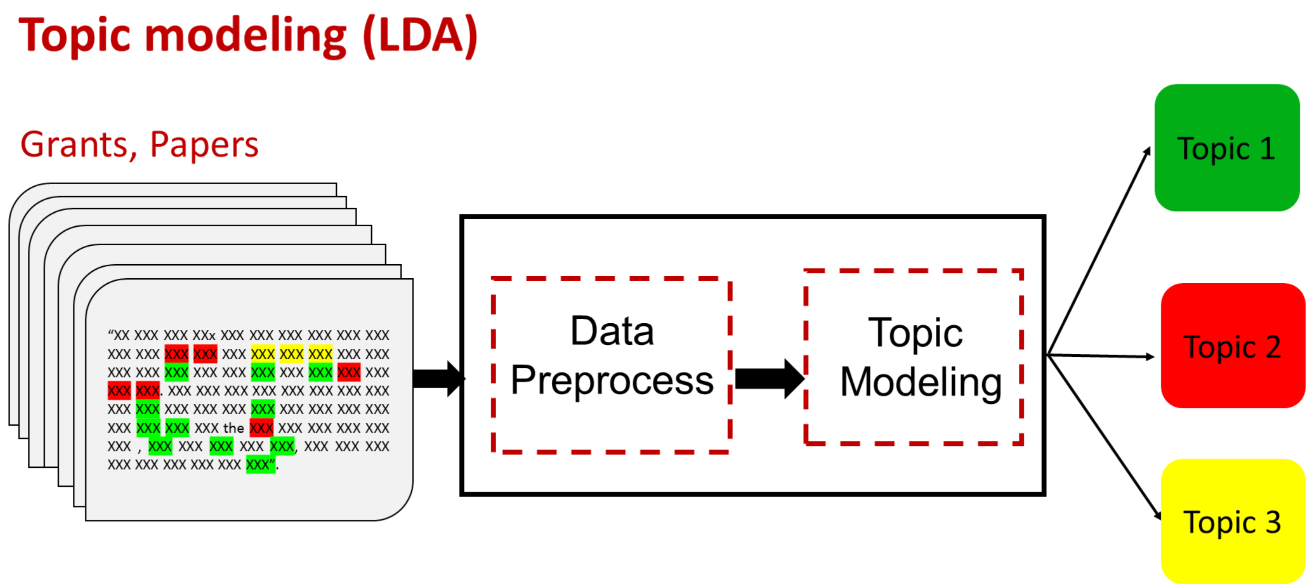

Figure 3-4 Effects of Scientific Business Knowledge and CEO Scientific Knowledge on the Probability of Novel Pursuits

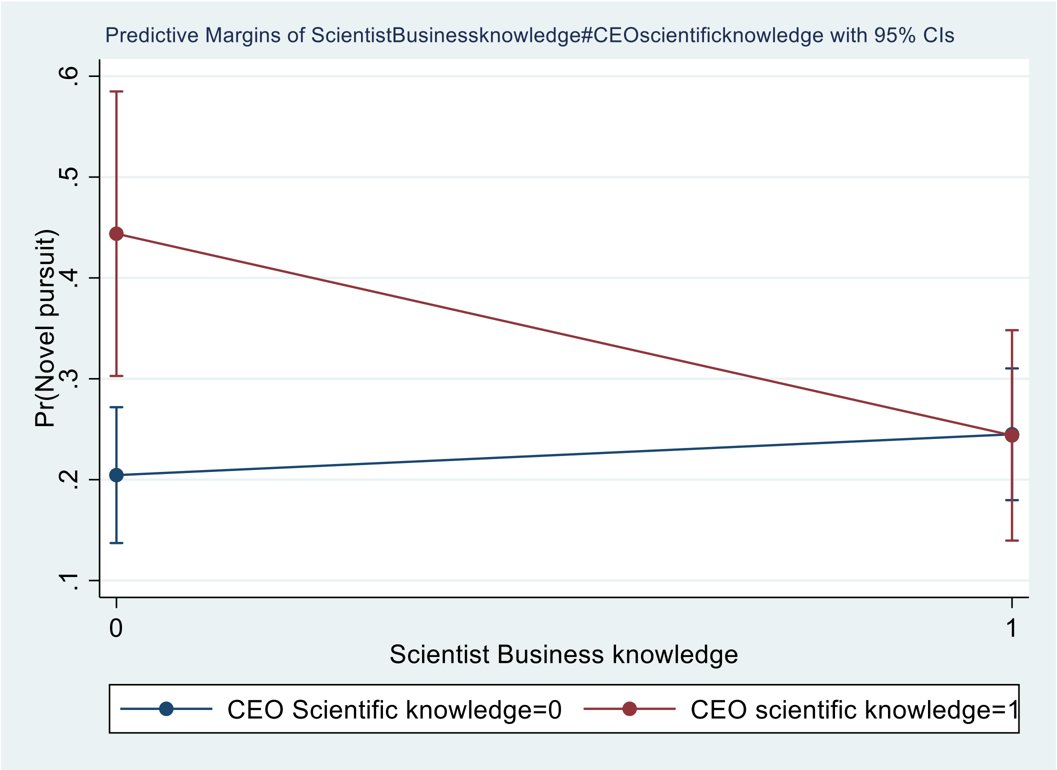

Table 3-1 Literature on the Role of Varied Knowledge Types

Study	Type of knowledge	Knowledge at Individual/Firm Level	Research Question	Empirical Setting	Key Findings
Conti et al. (2013) OrgSci	Technological knowledge	Individual	How does past stock of knowledge of an inventor impacts rate of new inventions and probability of an invention being a breakthrough?	5,144 European inventors using patents to identify past stock of inventions	Inventors with more patent stock develop higher rate of patents, but the probability of them being a breakthrough decreases.
Tzabbar (2009) AMJ	Technological knowledge	Individual	How does the type of knowledge that newly recruited scientists possess impacts firm technological repositioning?	2,643 biotechnology industry hiring using patent data to identify recruitment	Recruitment of scientists who possess technological knowledge that is distant from current knowledge of firms is positively related to technological repositioning.
Katila et al. (2017) AMJ	Domain knowledge	Individual	How do domain experts (i.e., end-users of products) in their different roles as inventors, executives, and board members impact innovation?	qualitative analysis of 231 surgical instrument ventures over 25 years	If such experts become inventors, they contribute to innovation outcome. Executives who are surgeon are not much likely to be helpful and they are likely to decrease innovation endeavors.
Ali & Gittelman (2016) Research Policy	Basic and clinical knowledge	Individual	What is the impact of possessing basic and clinical knowledge on probability of licensing?	patents and licenses of Academic Medical Centers (AMCs) for 30 years	If teams have clinical researchers, it is more likely that invention is licensed than teams who have basic scientists. They also showed if teams have both kinds of researchers it is not more likely to get licensing.

Baba et al. (2009) Research Policy	Basic and technological knowledge	Individual	What kind of scientists - based on the knowledge they possess- are more successful in research collaborations?	455 firms, photo catalysis industry in Japan, using patents and publications to measure scientist knowledge	Engaging in research collaboration with Pasteur researchers enhances research output, however, collaboration with star scientists has little influence on innovation outcome.
Subraminian et al. (2013) Research Policy	Basic and technological knowledge	Individual	How do different types of scientists in firms -in terms of scientific and technological knowledge they possess- impact innovation collaboration of firms?	Panel data, 222 firms, biotechnology, 1990-2000, using patents and publications of scientists	Bridging scientists complement alliance activities of firms. However, Pasteur bridging scientists (who have more inclination towards fundamental research) work the same as R&D alliances with universities (they are substitutes).
Sauermann & Stephan (2013) Org Sci	Basic, applied, development knowledge	Individual	How do industry and academic science differ?	survey data on around 5,000 scientists	Academia and industry are different along nature of work, workers, workplace, and disclosure of results
Roy & Sarkar (2016) SMJ	Technological knowledge and user knowledge	Firm	How does a firm face radical technological change?	robotics industry	Both upstream and downstream linkages contribute to firm performance when firms go through such changes.
Zhou & Li (2012) SMJ	Technological and market knowledge	Firm	How firms' knowledge base (depth & breadth) and mechanisms to integrate knowledge (i.e., internal knowledge sharing & external knowledge transfer) impact innovation generation?	Survey from high technology industry in China	Firms with broader knowledge are more likely to generate radical innovation if they have internal knowledge sharing. However, firms with deeper knowledge are more successful in radical innovation by acquiring knowledge of the market.

Table 3-2 Definitions and Measures of Variables

Variable	Definition	Measure
Novel pursuits	Innovation that "introduces a potential new technological trajectory" which is in contrast to incremental innovation which follows existing trajectories (Kaplan & Vakili, 2015: 1436).	Equals 1 if the grant/paper abstract was considered topic originating. For more details please refer to how novel pursuits were identified. 0 otherwise
Scientists' business knowledge and experience	Scientists' knowledge and experience related to business which could be knowledge and experience in marketing, operations, economics, etc.	Equals 1 if scientists had any business related education (e.g., MBA or economics), or functional roles related to business (e.g., operations, marketing roles), 0 otherwise
CEOs' scientific knowledge and experience	CEOs' scientific (basic science) or technological (applied research) knowledge	Equals 1 if CEOs had Ph.D. or scientific related roles (such as chief scientists), 0 otherwise
Management	Firms' management team expertise and capability	Rating of the firms' management team which was provided by NewSpace Global database (between 0 and 10)
Marketing	Firms' marketing expertise and capability	Rating of the firms' marketing capability which was provided by NewSpace Global database (between 0 and 10)
Capital	Firms' financial capability and strength	Rating of the firms' financial capability which was provided by NewSpace Global database (between 0 and 10)
Technology	Firms' technological capability and strength	Rating of the firms' technological capability which was provided by NewSpace Global database (between 0 and 10)
NSG position	Firms' position in the market in comparison to other firms in the industry	Firm position in the market that was provided by NewSpace Global database.
Revenue	Firms' revenue	Estimated revenue of firm that was provided by NewSpace Global database (in million).

Table 3-3 Descriptive Statistics and Correlations

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1	Novel pursuits	0.193	0.395	0	1								
2	NSG position ordinal	3.096	0.849	1	5	-0.064							
3	Estimated Revenue Ordinal	6.457	2.074	1	10	-0.086	0.546						
4	Management	4.507	1.368	0	8.2	-0.046	0.826	0.599					
5	Market	4.537	1.337	0	7.2	-0.101	0.775	0.529	0.878				
6	Capitalization	3.992	1.506	0	8.7	-0.046	0.828	0.585	0.844	0.872			
7	Technology	5.104	1.756	0	9.4	-0.102	0.811	0.693	0.873	0.801	0.831		
8	Scientist Business knowledge	0.451	0.497	0	1	-0.021	-0.024	-0.116	-0.037	-0.085	-0.092	-0.041	
9	CEO Scientific knowledge	0.391	0.488	0	1	0.044	-0.249	-0.151	-0.048	0.012	-0.134	-0.138	-0.012

Table 3-4 Logit Regression Results (Dependent variable= Novel Pursuits)

	Model 1		Model 2		Model 3	
NSG position ordinal=1						
NSG position ordinal=3	-0.689	(2.239)	1.260	(2.351)	1.959	(2.388)
NSG position ordinal=4	-1.251	(2.501)	1.037	(2.699)	1.837	(2.753)
NSG position ordinal=5	-0.925	(2.783)	1.405	(3.049)	2.751	(3.137)
Estimated Revenue Ordinal=1						
Estimated Revenue Ordinal=5	-0.243	(2.056)	-1.272	(2.128)	-1.409	(2.116)
Estimated Revenue Ordinal=6	1.347	(1.932)	1.717	(1.871)	1.605	(1.889)
Estimated Revenue Ordinal=7	-0.001	(1.968)	0.240	(1.836)	0.131	(1.879)
Estimated Revenue Ordinal=8	1.231	(1.964)	1.585	(1.899)	2.044	(1.968)
Estimated Revenue Ordinal=9	0.240	(1.844)	0.056	(1.728)	0.015	(1.747)
Estimated Revenue Ordinal=10	0.807	(2.059)	1.500	(2.015)	1.432	(2.053)
Management	0.200	(0.284)	0.330	(0.306)	0.267	(0.298)
Market	-0.531	(0.354)	-1.178**	(0.463)	-1.155***	(0.441)
Technology	0.134	(0.258)	-0.042	(0.265)	-0.029	(0.256)
Capitalization	-0.040	(0.376)	0.174	(0.395)	-0.020	(0.411)
Year=1984						
Year=1988	4.714***	(1.535)	4.755***	(1.551)	5.375***	(1.517)
Year=1991	4.828***	(1.128)	5.023***	(1.110)	5.406***	(1.110)
Year=1992	5.456***	(0.997)	5.427***	(1.027)	5.700***	(1.055)
Year=1996	3.298***	(0.821)	3.290***	(0.790)	3.627***	(0.858)
Year=1997	4.354***	(0.957)	4.294***	(0.891)	4.796***	(0.966)
Year=1998	3.952***	(1.030)	4.458***	(1.053)	4.860***	(1.090)
Year=1999	5.995***	(1.205)	6.124***	(1.158)	6.383***	(1.098)
Year=2000	3.463***	(0.747)	3.644***	(0.768)	3.605***	(0.776)
Year=2001	4.030***	(1.007)	4.801***	(1.100)	4.663***	(1.191)
Year=2002	3.135***	(0.871)	3.262***	(0.877)	3.285***	(0.895)
Year=2004	2.014	(1.247)	2.144	(1.307)	2.380	(1.465)
Year=2005	2.311**	(0.994)	2.406**	(0.975)	2.462**	(0.996)
Year=2006	3.026***	(0.816)	3.203***	(0.807)	3.218***	(0.821)
Year=2007	0.905	(0.858)	0.995	(0.830)	0.931	(0.829)
Year=2008	2.394***	(0.787)	2.429***	(0.767)	2.473***	(0.788)
Year=2009	1.718**	(0.733)	1.733**	(0.713)	1.669**	(0.717)
Year=2010	2.103***	(0.729)	2.177***	(0.722)	2.095***	(0.716)
Year=2011	1.839**	(0.836)	1.828**	(0.805)	1.688**	(0.835)
Year=2012	0.946	(1.000)	0.900	(1.049)	0.891	(1.109)
Year=2013	0.506	(0.701)	0.349	(0.683)	0.494	(0.727)
Scientist Business knowledge=1			-0.316	(0.329)	0.372	(0.391)
CEO scientific knowledge=1			0.951*	(0.570)	1.831**	(0.762)
Scientist Business knowledge=1*CEO scientific knowledge=1					-1.840**	(0.734)
Constant	-2.262**	(1.135)	-2.132*	(1.113)	-2.317*	(1.186)

Standard error in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 3-5 Multivariate Cox Regression Analysis (Dependent variable= Novel Pursuits)

	Model 1		Model 2	
NSG position ordinal=2	-0.316	(2283)	0.505	(2378)
NSG position ordinal=3	-0.221	(0.601)	0.898	(0.688)
NSG position ordinal=4	-0.814	(0.796)	0.513	(0.898)
NSG position ordinal=5	0.914	(0.909)	279.1***	(107)
Estimated Revenue Ordinal=1	18.77	(1119)	19.77	(1088)
Estimated Revenue Ordinal=2	0.306	(1254)	107.3	(1197)
Estimated Revenue Ordinal=3	0.064	(1181)	111.8	(1150)
Estimated Revenue Ordinal=4	-0.334	(1146)	0.102	(1115)
Estimated Revenue Ordinal=5	17.49	(1119)	18.4	(1088)
Estimated Revenue Ordinal=6	18.27	(1119)	19.38	(1088)
Estimated Revenue Ordinal=7	17.43	(1119)	18.33	(1088)
Estimated Revenue Ordinal=8	17.77	(1119)	19.01	(1088)
Estimated Revenue Ordinal=9	17.91	(1119)	18.63	(1088)
Estimated Revenue Ordinal=10	10.756	(1119)	17.98	(1088)
Management	0.251	(0.211)	0.185	(0.211)
Market	-0.541***	(0.17)	-0.813***	(0.185)
Technology	-0.142	(0.151)	-0.109	(0.154)
Capitalization	0.343***	(0.167)	0.388***	(0.164)
Scientist Business knowledge=1			-0.201	(0.181)
CEO scientific knowledge=1			0.949***	(0.262)
Scientist Business knowledge=1*CEO scientific knowledge=1				

Standard error in parentheses, * p<0.10, ** p<0.05, *** p<0.01

CHAPTER 4: PAPER THREE

A CONTINGENCY FRAMEWORK ON THE INNOVATION IMPACT OF STARS[6]

4.1 INTRODUCTION

"There is no shortage of fault to be found amid our stars"
- John Green, *The Fault in Our Stars*

Who wouldn't ask for a star performer in their organization? Stars are rare, high-achieving individuals who deliver an unmatched level of innovative value (Helft, 2011; Kehoe & Tzabbar, 2015). According to O'Boyle and Aguinis (2012) the high performing stars are so rare that their impact on firm-level outcomes is best understood as a power law distribution, implying that very few alpha-tail individuals outperform the other 99%. Then, over time, the perception that the focus on a "star system" (i.e., strategic human resource management systems that focus on hiring and retaining star employees) is indispensable to firm-level vitality has remained mostly undisputed (Wright, Coff, & Molierno, 2014), specifically in high technology industries in which stars are expected to make a large impact on firms' innovation (Aguinis & O'Boyle, 2014).

The problem is that star performers do not always produce starry results. New scholarly works have started to reveal counterintuitive, counterproductive aspects of stars (e.g., Asgari & Hunt, 2015; Kehoe & Tzabbar 2015), implying that stars need to be studied with much more scrutiny. Particularly, existing approaches to stars have not accounted for the unique impact star employees have on organizational innovation based on the *stage* of employment and *goals* of a firm. It is increasingly apparent that star systems are neither all favorable, nor all unfavorable

[6] This study is developed in collaboration with Dr. Richard A. Hunt.

(Asgari & Hunt, 2015), raising the question: what set of circumstances help or hinder a star's ability to elevate organizational outcomes?

Alert to the need for a more nuanced conception of star performers, our paper extends and enhances current literature by development of a contingency-based framework governing the impact of elite performers in the context of innovative pursuits. Our approach provides useful boundary conditions along two vital dimensions. First, we are concerned with the unique approach a firm takes towards organizational renewal; specifically, whether the use of stars is related to exploration or exploitation activities (Tzabbar & Kehoe, 2014; Groysberg & Lee, 2009). Existing literature has acknowledged the importance of the exploration-exploitation distinction at the firm-level (Gupta, Smith, & Shalley, 2006), but has not fully accounted for the differential impact of star-performers in each context. Second, we are concerned with the phase of an individual's tenure with an organization. Conceptual and empirical work in strategic human resources management (SHRM) has amply noted the evolving nature of employee-employer relationships across the lifecycle of an employee's tenure (Allen, 2006; Smither, 2003); but thus far, scholars have not sought to bridge the lifecycle of star performers to critical elements of a firm's innovative output. Doing so may provide important clues regarding the conflicting sentiments that characterize the literature on star performers. In an integrated fashion, we propose that a combination of organization-level contingencies -- related to a focus on either exploration or exploitation – and, employee-level contingencies – related to a star's stage of employment -- promote or inhibit a star's organizational impact. In this sense, we propound the notion that the facilitators and inhibitors of stars' effectiveness are likely to differ based on the continuously evolving nature of the organization-employee fit.

Our paper makes two important contributions. First, in addressing the gap on how, and to what extent, stars impact firm-level outcomes, we build a new framework illuminating the circumstances under which the organizational benefits of star performers outweigh the costs. In this regard, we contribute to the literature on star performers by providing boundary conditions that govern the favorable and unfavorable impact of stars, while advancing a theory of "non-uniformity," a predictive basis that accounts for changes in the organization-star relationship over time. Second, we extend literature on the determinants of innovative output (e.g., Austin 1993; Liebeskind, 1996; Ritala, Armila & Blomqvist, 2009) by modeling stars' impact as a function of the manner in which organizations pursue innovation. Our framework presents a useful alternative to the presumption that star systems are, by design, mission-critical, value-enhancing fountains of innovative output. Like all useful contingency frameworks, our boundary conditions offer important "guardrails" for organizations relying on stars not under the right conditions.

4.2 THE LITERATURE ON INNOVATIVE STAR PREFORMERS

Extant Thinking on Star-Powered Innovation

Innovation – involving the "generation, development, and implementation of new ideas or behaviors" (Damanpour, 1991) -- is indispensable to sustainable competitive advantage (Eisenhardt & Tabrizi, 1995; Porter, 2011). Innovation has long been known as the differentiating driver of economic growth (Schumpeter, 1942). To generate innovation firms have to recombine knowledge in novel ways (e.g., Kogut, & Zander, 1992). Knowledge as the main contributor to innovation (Nonaka, 1994), points out to human capital as the micro-foundational substance of a firm's capabilities (Felin & Foss, 2005), since individual abilities and interactions are a critical facet of generating knowledge (Felin & Hesterly, 2007). Star performers have long been viewed as crucial contributors to innovation (Aguinis & O’Boyle, 2014) as important generators of outstanding knowledge (Rothaermel, & Hess, 2007; Zucker, Darby, & Brewer, 1994). Stars are defined as individuals with exceptional performance who enjoy extraordinary visibility in the industry (Groysberg, Lee, & Nanda, 2008), with particular focus on high performance (e.g., O’Boyle, & Kroska, 2017) and high status (e.g., Prado & Ferraro, 2018). The common denominator among the varied perspectives is the largely unquestioned conviction that stars provide the great preponderance of an organization’s innovative capacity and output.

Scholarly works studying the impact of stars extends back to Whyte’s research, where he compared average and outstanding performers (1956). The dominant idea is that in static industries average workers are preferable, however, stars are crucial in fast-changing environments. According to Rosen (1981), stars’ productivity is so exceptional that their output cannot be substituted by other employees’ work. Hunter, Schmidt, and Judiesch (1990) showed the importance of stars in high complexity jobs where their productivity was found to be twice that of average workers. Wide acceptance of the ‘War for Talent’ – highlighted in McKinsey Consulting’s 1997 study – has heightened the focus on star power (Helft, 2011; Michaels, Handfield-Jones, & Axelrod, 2001), and the corresponding belief that stars are a material differentiator of organizational success or failure (Bedeian & Armenakis, 1998; O’Boyle, & Kroska, 2017). While the primary focus of stars research involves their out-sized productivity, other studies have investigated their high status, which is not necessarily a result of performance (e.g., Adler, 1985), or their potential for their output in the future (e.g., Feldman & Goldsmith, 1986; O’Boyle, & Kroska, 2017). Findings suggest that if creating value highly depends on individuals, the difference between stars and non-stars is perceived to be prominent (Groysberg et al., 2008).

Stars provide a valuable and rare opportunity for creating competitive advantage; which is in consistency with Resource Based View of the firm (RBV) (Barney, 1991). Since firms need to create and capture value, the potential influence of stars drives firms into development of SHRM systems for hiring and retaining elite performers (Kelley & Caplan, 1992; Tzabbar, 2009). Thus, star performers are known to be highly productive (Hess & Rothaermel, 2011), and extraordinarily hard to be replaced (Dierickx & Cool, 1989).

The Limits of Star Power

Empirically and conceptually, the supporting case for star systems seems strong, particularly in the context of a knowledge-based economy and alarming shortages of knowledge workers (Pobst, 2014). There is, however, evidence that this view may be under-nuanced as recent scholarship has tried to inject a more critical assessment into both the conceptualization of star systems and the organizational impact of star performers. Focusing on the importance of social mechanisms in generating new knowledge, Grigoriou and Rothaermel (2014: 587) introduced the concept of "relational stars" describing them as "[individuals] who have large, dense, or far-reaching networks of collaborators…. [those] whose collaborative behavior allows them to operate as the linking pins among internally distant and otherwise unconnected clusters of knowledge." Kehoe, Lepak, & Bentley (2016) proposed a new typology of stars, introducing "universal," "performance" and "status" stars, based on the combination of external status and task performance. Universal stars refers to individuals who have both exceptional performance and high external status. Performance stars refers to individuals who only have exceptional performance. Finally, status stars are those who have extraordinary external status because of networking capabilities, close ties with prestigious individuals, or previous exceptional performance.

In addition to these efforts to better define and describe stars and star systems a few studies have investigated possible pitfalls of star systems, testing the premise that instances exist in which stars may adversely impact their respective firms. For instance, Oldroyd and Morris (2012) noted that despite the benefits of having large social capital, stars are likely to suffer from information overload, which negatively impacts their performance, how they share information with others, and consequently performance of their organizations. Chen and Garg (2018) examined National Basketball Association (NBA) teams and showed that when star players are temporarily absent, teams' performance increases. This is mainly because average players take new roles and start to develop new routines and capabilities. There is research showing that stars limit the emergence of new leaders in firms (Kehoe & Tzabbar, 2015). Asgari and Hunt (2015) showed that contributions of non-stars can easily be crowded out with the presence of stars. In a similar vein, Prado and Ferraro (2018) showed that hiring a star can negatively impact organizational performance.

A summary of the literature on stars and their organizational impact is presented in Table 4-1. As the table reveals, there are marked inconsistencies among the definitions and the findings.

[Insert Table 4-1 about here]

As the details of this emerging stream suggest, the attempts to bring more nuance to the conception of stars' organizational impact have been fruitful (e.g., Kehoe et al., 2016; Grigoriou & Rothaermel, 2014); however, these refinements demonstrate more strongly than ever the need for a contingency framework through which to capture the varied, time-dependent and phase-dependent states that interact to create favorable and unfavorable conditions for stars' impact on organizational outcomes. In the dynamic context of innovation generation and innovation management, there is great need for a clear accounting of these contingent factors.

Moving toward a Contingency Theory of Stars

The lingering question to be drawn from extant literature is: How can we explain inconsistencies and disconnects between the intended impact and the actual impact of stars systems? Although scholars have recently sought to develop stronger explanations on how and why stars impact firms' innovation (e.g., Kehoe et al., 2016; Grigoriou & Rothaermel, 2014), this work has not evolved into a useful predictive framework. Greater distillation is required to take into account contingency factors that are relevant to the evolving nature of the individual-organization relationship. Responding to this need, our proposed framework elaborates upon the most relevant factors of this ongoing evolution: time and the goal-context of the firm.

Few scholarly works have pointed out to the importance of time on how stars impact firm outcomes (e.g., Chen & Garg, 2018; Groysberg et al., 2008; Tzabbar & Kehoe, 2014). Our main argument is that the stage of the tenure of a star performer works as a contingent factor that explains how elite performers' arrival, embeddedness, and departure can affect firms' innovation. This is because the varied phases of a star's fit with socio-cultural and political structures in organizations are unique in their respective impacts on interactions and outcomes. This, in turn, facilitates or hinders a star's effectiveness. In particular, we propose that stars have distinguishable impacts on explorative and exploitative innovation. As different activities in firms require different skills and social mechanisms (Tzabbar & Kehoe, 2014), stars will have differential impacts based on the innovative initiatives that firms pursue.

In the following sections, we detail the manner in which stars impact innovation processes and outputs while taking into account different phases of a star-employee's tenure, including the organization's fate post-departure. Taking a contingency approach (Donaldson, 2001), we develop a fine-grained framework to describe and assess stars' impact.

Phase-Dependent Determinants of a Star's Impact on Innovation

Given the conflicting perspectives regarding the potential value of high-performing individuals, we expect that phase-dependent shifts occur in an individual's relationship with their firm, spanning the complete lifecycle of the individual's tenure; shifts that affect an individual's impact on organizational outcomes. The direct and indirect impact of stars will vary as a consequence of differing levels of social and structural fit with the organization, aspects that we believe vary by phase, tenure, and an organization's strategy concerning innovation. Accounting for this set of conditions shifts away from sole preoccupation with individual performance to one that incorporates the social context, including a star's impact on others. Our efforts to incorporate social-contextual factors is consistent with recent research on stars and talent management (e.g., Minbaeva & Collings, 2013; Somaya & Williamson, 2011) that has begun to shift from a singular focus on the exceptional capacity to generate innovation to a model that also incorporates the ability to handle knowledge flows and social interactions (e.g., Grigoriou & Rothaermel, 2014); thereby taking into account emotional and social intelligence, as well. Research suggests that stars tend to impact social mechanisms associated with new knowledge generation through their presence and departure due to their exceptional status (e.g., Prado & Ferraro, 2018). Thus, we argue that stars' fit with the organization and their impact on social mechanisms and knowledge generation are likely to vary over time and are likely to be as impactful as the innovations that they generate.

Such moderated impacts can best be treated by taking a contingency-based approach (Mone, McKinley, & Barker, 1998), the main idea of which is that there are contingencies inside and outside firms that characterize multi-level phenomena. Contingency perspectives are based on the notion that there is not a unique best approach to find the fit among variety of organizational factors in order to generate superior performance (e.g., Donaldson, 2001). As such, any viable framework for a robust assessment of a star-employee's impact must account for the evolving fit (or misfit) between a star and phase-dependent changes in an organization's structures, aims, and social dynamics. Until now, we are not aware of any scholarly work that develops a contingency framework to explain how stars impact firms' innovation. By considering the evolving interactions of stars, we offer a useful basis for explaining the conflicting views on stars' impact.

Context-Dependent Determinants of a Star's Impact on Innovation

In addition to focusing on how stars' impact differs based on phase-dependent factors, we also focus on the role of an organization's innovation aims. There is high emphasis on distinctions between exploitative and explorative innovation (March, 1991). Exploration, refers to the search for novel knowledge which is outside and beyond the existing knowledge domain of firms, and exploitation, refers to the search for novel and new knowledge within current boundaries of knowledge of firms (Levinthal & March, 1993; March, 1991). Exploration and exploitation constitute the two broad activities firms undertake in order to generate innovations. The specific proportion of each is often a function of whether an organization is seeking radical breakthroughs or incremental modifications to dominant designs (Hunt, 2013, 2018). Few organizations are solely engaged in either exploration or exploitation, thereby placing a premium on the organization's effort to simultaneously be innovative by developing new products and services and benefit from returns to scale, as has been explored in the ambidexterity literature (Raisch & Birkinshaw, 2008).

Importantly, ambidexterity has little chance of coming to fruition if an organization's stars are misaligned during any phase of innovation, given the fundamental differences in resource configuration and operationalization -- as well as varying roles of stars -- during explorative and exploitative processes. For instance, Groysberg and Lee (2009) showed that when stars move to new companies, firms exhibit a short-term decline in exploitative capacity, but a long-term decline in explorative capacity. Similarly, Tzabbar and Kehoe (2014), examine the impact of a star's departure as a function of organization's explorative and exploitative focus.

4.3 THEORY DEVELOPMENT AND PROPOSITIONS

As the foregoing discussion reveals, stars and star systems are neither a clear asset nor a clear liability. Rather, the determination of a star's impact on the innovative output of an organization is tied to a multiplicity of inter-related factors, the substance of which is captured in Figure 4-1. Particularly, the nature of a firm's innovation focus and the employment lifecycle phase of the star employee suggest the need for boundary conditions concerning stars' value.

[Insert Figure 4-1 about here]

The illustration captures the essence of the star performer paradox; that is, stars are at once a desirable, perhaps even an indispensable, source of innovation, but they are also problematic. The unaddressed questions derived from the crosscurrents depicted in in Figure 4-1 suggest the need for a contingency approach to the organization-star fit; an approach that should better account for the manner in which organizational structures and social mechanisms facilitate or inhibit the innovative impact of stars. In the following section we develop just such a contingency framework.

Contingent Model of Stars' Impact on Firm Innovation

We focus on large established firms as we develop this framework. This is because large incumbents are much more likely to face the simultaneous expectations of producing high returns while also delivering novel innovations. We also focus on stars who have both exceptional performance and high internal and external status. As noted earlier, our contingency model posits three key evolutionary phases: (a) onboarding, (b) socialization and embeddedness, and (c) departure.

Contingent Phase 1 - Onboarding

Hiring is one of the strategies firms use to acquire new knowledge that is necessary for innovative endeavors of firms, but difficult to develop internally (Almeida & Kogut, 1999; Tzabbar, Silverman, & Aharonson, 2007; Hess & Rothaermel, 2011). The onboarding stage sets the relationship that the newly hired individual and employer will develop. Successful recruitment of knowledge workers has been shown to be an indispensable facet of a firm's ability to build internal capabilities (Rosenkopf & Almeida, 2003) and compete effectively with firms (Dorsey, 2003). However, successful assimilation of newly hired human capital resources is far from a *fait accompli* (e.g., Tzabbar, 2009). For this reason, stars' impact is best understood in the specific social context (e.g., Groysberg, Polzer, & Elfenbein, 2011; Grigoriou & Rothaermel, 2014) that may be relevant to the "onboarding" process.

Contingent effects of onboarding on exploration. In the search for innovation, firms try to go beyond their established knowledge bases through explorative activities (Tzabbar, 2009). Based on the knowledge-based view, the search for knowledge outside an organization's immediate purview is a precondition to attaining and maintaining a sustainable competitive advantage (Teece, Pisano, & Shuen, 1997). As firms need to change, substitute, supplement, or eschew existing capabilities in favor of new ones, the challenges confronting an organization are how to conduct a fruitful exploration and how to effectuate purposive discontinuity with existing knowledge and familiar technologies (Kogut & Zander, 1992). The perceived and actual constraints on existing routines and capabilities (Nelson & Winter, 1982), and the routinized search behaviors of employees and teams (March, 1991), make even well-structured, well-supported attempts to achieve transformative ends difficult, and often impossible. Given the formidable nature of these obstacles, firms often look outside their respective organizations for fresh insights and capabilities by may hiring star scientists and other “knowledge carriers” (Almeida & Kogut, 1999; Hess & Rothaermel, 2011) in the search for new knowledge. “Learning by hiring” literature suggests that attracting elite performers could work as a viable means to bolster the explorative capacity of a firm. This is especially important when stars possess useful knowledge from distant, unrelated domains. However, “purchasing knowledge” through hiring may not be sufficient to integrate and deploy a star’s knowledge. Onboarding, which involves a multiplicity of processes once a new employee is hired, can be socially complex – much more so when the new hires represent a significant, strategically important departure from existing processes and perspectives (Almeida, Dokko, & Rosenkopf, 2003; Tzabbar, 2009). These complexities suggest the need for boundary conditions. We see three primary reasons why newly on boarded stars will have only an incrementally positive impact on a firm’s explorative outcomes.

First, although stars are expected to directly impact the exploration endeavors of firms by developing new knowledge search routines, existing structures and processes of a firm are likely to hinder stars’ ability to develop new search routines in the period after being hired, even when new strategic directions have the full support of the firm’s executive committee. Much of this inertia is an unintended vestige of legacy systems. As Song, Almeida, & Wu (2003) pointed out, pre-existing research pathways exert important constraints on the extent to which new scientists are able to reorient the explorative activities that will eventually impact a firm’s innovative outcomes. In spite of the fact that the development of new search routines requires the assimilation of knowledge from outside the firm's established routines and beyond existing competencies (Chen & Garg, 2018), existing structures hinder stars' ability to institute new search routines.

Second, in addition instituting transformative approaches by leveraging explicit knowledge, stars are expected to indirectly impact the exploratory activities of firms through tacit knowledge spillovers. This, too, faces socially complex facilitation and inhibition, since knowledge spillovers emanating from new hires is dependent on their interactions with incumbent scientists (Mass & Moretti, 2009). This social complexity is likely to be more significant when stars are tasked with instigating relative distant searches, involving knowledge spillover substance that is unfamiliar to the existing organization. The difficulties are borne out in recent research. For example, Prado and Ferraro (2018) showed that hiring stars lead to very little knowledge spillover for the hiring firm. Agarwal, McHale, & Oettl (2017) showed non-positive impacts of new hires on incumbent scientists' performance; specifically, if they have knowledge in unrelated domains. Tzabbar, Silverman, & Aharonson (2007) showed that beneficial knowledge assimilation during the onboarding phase is extremely difficult. Almost uniformly, new citations are generated primarily by newly hired scientists rather than incumbent scientists. Tzabbar (2009:874) noted:

> "the social and technological structures within which innovation efforts take place will influence scientists' ability and willingness to recombine their knowledge and hence will affect the likelihood of successful transformation of a firm's technological capabilities".

Thus, the knowledge assimilation of new hires, especially in distant or unrelated domains is dependent on individuals' capacity and motivation to integrate new knowledge (Kogut & Zander, 2009). Prior research suggests that star scientists are less likely to be motivated to share their knowledge (Overbeck & Park, 2006), meaning that it is less likely that stars will impact firms' explorative activities through knowledge spillovers.

Finally, we believe that a contingent model of stars' impact must establish boundary conditions related to the onboarding phase of employment due the apportionment and deployment of social capital. Although stars tend to benefit from a degree of perceived social capital (Oldroyd & Morris, 2012; Kehoe et al., 2016), and enjoy unusually good access to beneficial network resources, the reconfiguration and mobilization of these resources in the onboarding phase is elusive. Recent hires, who are inherently in a state of professional reconfiguration as they switch employers are slow to mobilize their existing network resources and the tacit knowledge housed in those networked relationships (Kehoe et al., 2016), thereby limiting the speed and extent to which hiring firms benefit from stars in the onboarding phase.

Taken together, these three factors lead to the argument that while stars are, on average, likely to have a positive impact on the effectiveness of the hiring firm's explorative search due to the fresh perspectives and processes they bring to the new employer, the positive effects are only incremental, not transformational. As discussed above, this relatively tepid response is due to the fact that although stars have some impact by bringing their knowledge and expertise, they are unlikely to have a direct, transformative impact, which would be evidenced directly through the development and implementation of radically new search routines, or indirectly through the collateral impact of knowledge spillovers on pre-existing employees. More formally, we propose:

Proposition 1: *Onboarding a star scientist is likely to incrementally enhance a firms' exploration outcomes.*

Contingent effects of onboarding on exploitation. The totality of any firm's innovative output involves an evolving combination of explorative and exploitative processes, the former involving search for more distant opportunities and the latter leveraging resident knowledge for more proximal opportunities. Newly hired stars – even those principally hired to revitalize explorative innovation -- are also like exert influence on the manner in which firms mobilize resources and knowledge in familiar technological domains (Groysberg & Lee, 2009), by directly or indirectly impacting a firm's exploitative innovation. Here too, we argue that a star's impact is likely to be complex. In fact, while we expect socially complex, inter-relational factors to render a star's impact incrementally positive in Proposition 1 above, we expect stars to have a net negative impact on a firm's exploitative endeavors. There are two main reasons for this. First, exploitation is, by its very nature, path-dependent (March, 1991; Chen & Garg, 2018), meaning that prior search outcomes of search, and the attendant capabilities and routines that underlie those outcomes, become the starting point of all subsequent activity, especially as routines and processes are formalized in order to achieve increasing returns to established lines of business. Since new hires are perhaps less familiar with firms' past research, there is a period of transition during which the star and organization need to establish formal and informal grounds to achieve assimilation and knowledge transfer. A firm focus on exploitative processes exacerbates this disconnect during the onboarding phase. For instance, Song et al. (2003) showed that the citation of new scientists' prior patents is less likely after hire, especially when firm's research is path-dependent (i.e., when firms exploit current technological domains). This is also consistent with prior research showing that stars' performance tends to drop when they move to new firms because they lack firm-specific knowledge that is germane to exploitative processes (Groysberg, Lee, & Nanda, 2008).

The second reason that onboarding stars will have a net negative impact on the exploitative capacity of a firm relates to the pre-existing internal mechanisms and processes firms rely upon to diffuse knowledge. These formal and informal knowledge sharing rules, mechanisms, norms and routines undergird firms' ability to exploit current knowledge domains. When stars are hired, they can cause disruptions to knowledge sharing routines and, perhaps most importantly, they can adversely affect a firm's absorptive processes (Song, Gnyawali, Srivastava, & Asgari, 2018). Firms' absorptive processes – the "internal procedures and practices related to knowledge diffusion" (Song, et al. 2018: 2348) -- are indispensable to the exploitation of familiar, proximal knowledge domains. Disruptions to these vital processes can result from stars' unique status both internally (Kehoe et al., 2016) and externally in association with their broad visibility in the industry (Groysberg et al., 2008). Under even the best circumstances, high status has the potential to inject unwanted asymmetry into the reward and recognition systems of an organization (Prado & Ferraro, 2018). Disruptions of this sort can adversely impact firms' ability to sustain internal mechanisms, routines, efficient knowledge exchange, sharing mechanisms, and existing social structures – in short, the vital mechanisms enabling absorptive capacity (Bendersky & Hays, 2012; Groysberg, Polzer, & Elfenbein, 2011).

Taken together, we argue that onboarding stars tends to negatively impact firms' exploitative outcomes.

Proposition 2: *Onboarding a star scientist is likely to incrementally negatively impact firms' exploitation outcome.*

In the next section, we look into the impact of star employees during the embeddedness stage.

Contingent Phase 2 – Embedded Presence

Employees' embeddedness has been addressed extensively in the literature (Mitchell, Holtom, Lee, Sablynski, & Erez, 2001; Lee, Mitchell, Sablynksi, Burton, & Holtom, 2004), but with scant attention to the specific challenges and opportunities related to star employees. According to Mitchell et al. (2001), embeddedness refers to forces that inhibit employees from leaving their job and encourage them to stay on the job. The embedded phase is the period during which stars either do, or do not, establish a lasting fit with the organization. In this sense, regardless of the challenging distractions, impediments, and sub-optimalities that mark many facets of the onboarding phase, we argue that the embeddedness phase embodies the defining elements of each star's favorable or unfavorable legacy with a firm.

Contingent effects of embeddedness on exploration. Following existing work on SHRM (Ng & Feldman, 2007), we argue that when stars become embedded, they tend to have a different impact in comparison to the time they are newly hired (Groysberg & Lee, 2009). We argue that in this stage stars' impact on the exploration endeavors of firms is substantially positive for the three reasons. First, by definition stars possess unique value since they are in the top of performance spectrum (O'Boyle & Aguinis, 2012; Kehoe et al., 2016). Stars' out-sized ability to identify and engage new knowledge domains constitutes the main driver of their superior performance (Call, Nyberg, & Thatcher, 2015; Tzabbar & Kehoe, 2014). Since such a high-level of expertise requires a significant amount of time and resources, stars have a demonstrated ability and willingness to leverage the tacit knowledge (Hitt, Bierman, Shimizu, & Kochhar, 2001; Kehoe et al., 2016) they have acquired in novel ways. Once organizationally integrated during the embeddedness phase, stars enhance and extend a firm's absorptive capacity to identify, value, and transform external distant knowledge (Zahra & George, 2002). The problem-solving behaviors of stars guides their exploratory search processes and helps stars succeed in such endeavors (Fleming & Sorenson, 2004). Given that exploration is associated with greater uncertainty and more inconsistency than exploitation (Fleming, 2001), stars' experience, ability, motivation, and expertise to deal with such uncertainty make them valuable for exploratory search processes. Also, since stars have more control over resources and autonomy in choosing their research agendas (Kehoe & Tzabbar, 2015), they are likely to lead more explorative projects (Conti, Gambardella, & Mariani, 2014). Typically, top managers establish the strategic direction of research in firms (Panico, 2009) and determine the allocation of resources (Conti et al., 2014). While existing literature suggests that many exploratory projects are not pursued because managers question their potential value, studies suggest that the natural proclivity towards managerial caution is substantially mitigated when stars are involved in exploratory projects, due to of their perceived skill and insights (Conti et al., 2014),

Second, stars have the capacity to add value through their external status, which provides access to valued resources and social ties. Network research suggests that the content of social network resources impacts the speed and value of knowledge scientists possess (Lee, 2007). It also facilitates access to tangible and intangible resources (Liebeskind, Oliver, Zucker, & Brewer, 1996; Hess & Rothaermel, 2011). Scientists who have high status and wide visibility in an industry have a broader connection with scientific and business community. This, in turn, makes it possible to remain well-versed in cutting-edge knowledge, which is vital to exploratory search, requiring 'novel stimuli' and the ability to discard obsolete knowledge (Dane, 2010). Thus, key star assets that offer relatively little value in the onboarding phase, have the potential to benefit both the star-employee and the organization when embeddedness takes root.

Finally, stars are predicted to add value through their impact on exploratory innovation during the embeddedness stage because they are highly adept at developing new search routines (Chen & Garg, 2018). Search in organizations is inherently governed by capabilities and routines (March, 1991). In order to gain competitive advantage, firms create more effective routines to explore new knowledge domains. The role of a firm's human capital in the selection of such exploratory search routines is well-supported (Nelson & Winter, 1982), as is the important role of star performers in developing and selecting routines to generate innovation (Chen & Garg, 2018). In knowledge intensive industries, stars have been shown to be significantly more influential in defining and selecting routines to search for novel ideas beyond existing knowledge boundaries.

Proposition 3. *A star's embedded presence is likely to substantially increase the exploration outcomes of firms.*

Contingent effects of embeddedness on exploitation. Innovation is often characterized by complex combinations of individual genius and team-oriented organizational collaborations (Kogut & Zander, 1992). The nature of innovative pursuit by organically formed work group (Gibson & Vermeulen, 2003) entails a high degree of knowledge-sharing (Hargadon & Sutton, 1997), which suggests the need for a more nuanced investigation of stars' impact on existing and proximal knowledge stocks after a star enters the embedded phase of employment. In marked contrast to the significant benefits accrued to firms in the pursuit of explorative innovation by embedded stars, we there are confounding tradeoffs when embedded stars take up exploitative innovation through existing processes and more proximal search aims.

On the one hand, stars possess the rarefied ability to generate novel ideas that are highly valuable for firms (Grigoriou & Rothaermel, 2014). Similarly, stars' high productivity impacts the ability of firms to exploit current knowledge domains by increasing firms' knowledge base and current knowledge stocks of a firm; both of which are necessary for knowledge exploitation through the combination transformation, and redirected deployment of processes supported by existing knowledge domains. This makes stars difficult to replace, especially when they become embedded in the firm and their knowledge is assimilated (Dierickx & Cool, 1989).

On the other hand, stars' high internal status (Kehoe et al., 2016) leads to status asymmetry in firms (Groysberg et al., 2011). This can be problematic in the way that is can disrupt knowledge sharing routines that are required to exploit existing knowledge domains. This is especially a concern when stars need to work closely with other scientists. Prior research on stars has paid limited attention to the tradeoff between the great value of a star's skills and the related impact on the collaborative nature of innovation generation (Call, Nyberg, & Thatcher, 2015). Given the importance of resource and social dependencies (Tzabbar & Kehoe, 2014), a contingent model of stars' impact needs to contemplate and incorporate this tradeoff.

Innovation requires an effective collaboration among individuals to go beyond the narrow application of existing knowledge (Kogut & Zander, 1992). Research has shown that value-creating knowledge requires team processes (Wuchty, Jones, & Uzzi, 2007), particularly in the context of more local search (i.e., exploiting current knowledge domain). Knowledge accumulation (Murray & O'Mahony, 2007), knowledge sharing (Hansen, 1999), knowledge transfer (Tsai & Ghoshal, 1998), knowledge recombination, and the diffusion of knowledge (Galunic & Rodan, 1998), are each socially intensive processes (Nahapiet & Ghoshal, 1998) which are prerequisites to exploitative knowledge creation. According to Gardner, Gino and Staats (2012), exploitative innovation requires attentiveness to how each member's contributions are balanced through communication, coordination, and mutual support. Absent these social engagement mechanisms, firms run the risk of being "star struck," resulting in a failure to generate operational and financial gains. Examples of these effects include famously unexploited developments, such as Xerox's Palo Alto Research Center in the 1980's (Weiser et al. 1999), which developed but did not capitalize on numerous personal computing breakthroughs, underscoring the organizational and cultural challenges of star systems (e.g., Overbeck, Correll, & Park, 2005). Central to this is the effective collaboration of stars with others. According to Hambrick (1994), stars may be less willing to cooperate, share information, make joint decisions, and behave in a way that supports interdependent tasks. Additionally, when stars believe that sharing resources to other scientists is inconsistent with the goals of driving their own research idea, they may become less willing to nurture collaborations with non-stars (Overbeck & Park, 2006), partially as a function of ego (Hambrick, 1994), and partially as function of efforts to protect stars' privileged status (Hogan & Hogan, 1991).

Studies have also found that star systems unwittingly crowd out valuable contributions from non-stars (Asgari & Hunt, 2015). The rationale undergirding star systems of corporate innovation is that firms will realize the highest achievable "bang for the buck" by investing heavily in a small population of talented individuals (Aguinis & O'Boyle 2014), but the asymmetric commitment of resources may also create an undesirable power imbalance in the organization, particularly when stars believe that sharing resources is at odds with their unique status in the firm (Overbeck & Park, 2006). Star systems tend to reinforce the notion that high-achieving innovators are "made" not "born" (Chen & Garg 2018); but, in actuality, the asymmetric allocation of resources to star performers simply makes the superior performance of stars a self-fulfilling cycle; that is, stars receive more resources and attention, which allows they to perform better, which invites still more resources.

Considering the tradeoff between positive and negative impacts of embedded stars on exploitative innovation, we see a management challenge that must take into account two contrary forces. Without question, high-performing, embedded stars can exert a favorable impact on local search using existing knowledge, but only to the extent that they possess high social collaboration skills (Grigoriou & Rothaermel, 2014). Local search is heavily reliant upon deep organizational knowledge of a domain and efficient processes that engage a wide array of internal stakeholders. For this reason, we argue that embedded stars have a positive impact on exploitative innovation outcomes, but decidedly less do than when the firm is pursuing exploratory aims. This is primarily a consequence of the challenges in navigating social complexity by the star and the firm:

Proposition 4: *A star's embedded presence is likely to modestly increase the exploitation outcomes of firms.*

In the next section, we study the impact of star performers in the final phase of their relationship with an organization, that being the period after their departure.

Contingent Phase 3 - Departure

Employee mobility has been studied extensively both for stars and non-stars (Hausknecht & Holwerda, 2013; Park & Shaw, 2013). Employees' departure is an important stage as it often constitutes the loss of knowledge and skills and, oftentimes, the transfer of knowledge to competitors (Hunt, Asgari, Townsend, & Lerner, 2018; Rosenkopf & Almeida, 2003). Since star scientists are often known as both the primary carriers of knowledge and a wellspring of superior performance (Almeidia & Kogut, 1999), star departures are often depicted as a critical event for firms. As with the earlier phases of employment – onboarding and embeddedness – the reality is more interesting and more complex. Consistent with other facets of our contingency model, we argue that the departure of stars will have varied impacts on the firm.

Contingent effects of departure on exploration. The net effect of star's departure on exploratory endeavors is expected to be negative. There are a couple reasons for this. First, exploration requires unique vision and tacit knowledge and capabilities in making connections in distant domains. The complexity, scarcity, uniqueness, and tacitness of stars' knowledge in largely unpredictable tasks make their extraordinary abilities more difficult to replace (Dierickx & Cool, 1989). Stars' tacit knowledge and unusual ability to generate novel insights is especially important for effective exploration gained through 'learning by doing' (Tzabbar & Kehoe, 2014; Von Hippel, 1988). Since exploratory activities are inherently uncertain (Fleming & Sorenson, 2004), firms often rely on stars' knowledge to overcome the uncertainty in the innovation generation process

(Kehoe & Tzabbar, 2015) by gaining additional insight over time that enables them to transform uncertain, ambiguous, or equivocal search landscapes into problems of complexity, which are more amenable to the development and application of toolsets (Townsend, Hunt, McMullen & Sarasvathy, 2018). The ability of stars to confront the "knowledge problems" identified by Townsend and colleagues (2018) is a central source of stars' value and the primary cause of the value that is lost on their departure.

Over and above these internal impacts, stars' connections, social capital, and enviable access to tangible and intangible external resources (Kehoe et al., 2016) enable them to identify and play leadership roles in future exploratory research. When stars leave the organization, their scarce knowledge is lost together with their social capital. Also, firms need to continually renew their respective search routines as technologies, organizational forms, and business models constantly change (Hunt & Ortiz-Hunt, 2017). Firms rely on their valuable human capital, and particularly stars, to develop routines (Asgari & Hunt, 2015). A star's departure shows the loss of crucial knowledge and expertise that impact explorative activities (Stuart, 2017).

We argue, then, that a star's departure results in the loss of individual skills that are hard to replace and valuable social capital, and a disruption to search routines due to the centrality of stars to critical routines. As a result, organizational exploratory performance following the departure of a star, is likely to fall precipitously.

Proposition 5. *The departure of a star is likely to greatly decrease a firm's explorative outcomes.*

Contingent effects of departure on exploitation. Deep knowledge possessed by top performers is an important driver of exploitation (Griffith & Sawyer, 2010; Tzabbar & Vestal, 2015). Losing top performers and their deep knowledge leads to organizational deficiencies in the successful recombination of knowledge; but, as we witnessed earlier, there are social implications of star systems that do not always facilitate the aims of exploitative innovation. Once again, then, the impact of a star departure is likely to be complicated.

Ordinarily, when top performers leave the organization, the loss of the knowledge and capabilities constitutes a severe blow to the parent organization, since both deep and tacit knowledge may be permanently lost (Hitt et al., 2001). However, this may not be the whole story in the context of more proximal innovation searches using existing knowledge, since the supporting processes of exploitative innovation require a significant amount of knowledge transfer and knowledge sharing (Hargadon & Sutton, 1997). In short, effective collaboration among employees is vital. When stars depart, the status asymmetry and its negative consequences for knowledge sharing are alleviated. The absence of high-status asymmetry provides a renewed openness for individuals to more effectively communicate, share knowledge, foster the development of shared understanding, and insure joint involvement in decision making (Van der Vegt, De Jong, Bunderson, & Molleman, 2010). This favorable cascade is likely to facilitate efficient implementation and smooth functioning of routines to conduct local searches exploiting existing knowledge domains (Tzabbar & Kehoe, 2014).

Stars leaving the organization will also reduce power imbalance. As noted previously, the favored status stars enjoy brings them both internal and external recognition (Bunderson, 2003; Kehoe et al., 2016). By attracting and controlling key organizational resources (Kehoe & Tzabbar, 2015; Zucker Darby, & Torero, 2002), stars and their respective organizations may discount innovative contributions by other individuals (Adsgari & Hunt, 2015). When organizational resources and management attention are disproportionately allocated to stars, the prospects of non-stars are not only dramatically limited (Kehoe & Tzabbar, 2015), but they may be simply crowded out altogether (Asgari & Hunt, 2015). By occupying central roles (Paruchuri, 2010) and by captivating the prestige that makes stars admirable role models (Thye, 2000), firms deprive non-stars from encouragement and opportunities, making it far less likely that non-stars will pursue their own research ideas (Kehoe & Tzabbar, 2015; Huckman & Pisano, 2006). However, stars' departure is likely to lead to more balanced resource distributions, which reduces opportunistic behavior and task conflict. In turn, other knowledge workers are more willing and able to activate socially driven arrangements within the firm towards value-creating processes using existing knowledge stocks (March, 1991). When stars depart, we predict that the adverse impact losing their novel insights and capabilities will be favorably mitigated by the reduced organizational stress and by the creation of opportunities for others, who were previously crowded out through an allocation of resources heavily tilted towards star performers.

Proposition 6: *The departure of a star is likely to incrementally increase a firm's exploitation outcomes.*

The summary of our six propositions is presented in Table 4-2.

[Insert Table 4-2 about here]

4.4 DISCUSSION

The prevailing view of star performers – in sports, acting, business, science, academia, government, or virtually any other field -- is that they are indispensable. The general narrative is that stars produce exciting results and organizations are worse off without them. Our contingent model of star impacts suggests that this perspective suffers from several important flaws. At a minimum, there are important boundary conditions to consider.

As we have noted from the outset, the impact of stars and average workers has long been examined in management studies, economics, and social psychology (e.g., Adler, 1985; Feldman

& Goldsmith, 1986; Rosen, 1981; Whyte, 1956). Explicit in most of this work is the critical assumption that firms can and should prefer stars to non-stars, an assumption that has not been subjected to rigorous scrutiny. However, recent research has started to contemplate counter-intuitive, counterproductive facets of stars (Oldroyd & Morris, 2012; Kehoe & Tzabbar, 2015; Asgari & Hunt, 2015; Prado & Ferraro, 2018; Chen & Garg, 2018). For example, Tansley, Kirk, & Tietze (2013) point to an "over-emphasis on elite talent" in current economy. Recent scholarly work on stars suggests the need for a thorough reframe on the importance of star systems as the main prerequisite for successful innovation.

Despite escalating calls for a more nuanced approach to the role of stars, management research suffers for want of defining framework on the circumstances under which the benefits of having star performers do or do not outweigh costs of having them in the firm. To date, the focus has been on their extraordinary performance (Aguinis & O'Boyle, 2014; Groysberg et al., 2008; O'Boyle & Aguinis 2012), while only limited attention has been paid to vitiating impacts on the social fabric and innovative output of firms (e.g., Prado & Ferraro, 2018; Kehoe & Tzabbar, 2015).

In this study, we have tried to address the increasingly inconsistent views of star systems by specifically focusing on a context of central importance to firms: their innovative pursuits. The question that motivates this paper is: How and under what conditions are stars likely to have a positive or negative impact on innovation? In addressing this question, we have developed a new perspective on how stars might impact firms' innovation endeavors. Our contingency framework incorporates temporal considerations across the lifespan of the star-organization relationship – onboarding, embeddedness, and departure – as a variable that we predict will moderate innovative outputs. Our theory posits an evolving set of conditions wherein stars have decisively positive impacts during some phases of their life cycle, and decisively negative impacts during other phases. The second dimension of our contingency model takes into account a firm's innovation context involving the promotion or hindrance of innovation depending on two types of innovation aims, exploitation and exploration; where exploitation refers to search within current knowledge domains of the firm, and exploration refers to search outside the current knowledge domains of the firm (March, 1991). Each of these contingencies invite a fresh set of conditions that dictate the degree of fit between a star and an organization's social and structural mechanisms, which variously inhibit and facilitate performance across each employment phase in dynamic fashion. The summary of our propositions is shown in Figure 4-2.

[Insert Figure 4-2 about here]

Implications for Research

Focusing on innovation as the crucial nexus of star performers and firms, we contend that the presence of stars may, under a contingent set of circumstances, generate significant costs, significant benefits, or quite often, a significant mixture of both. In this sense, our framework has potent implications for scholars and practitioners. Addressing the question of how and under what conditions star performers benefit or harm firm outcomes addresses a gap in the field's conception of star performance in the context of perpetually evolving organizational aims and structures. Our framework bridges the literature on SHRM (Elfenbein & Sterling, 2018; Tzabbar, 2009), innovation (Kehoe & Tzabbar, 2015; Tzabbar & Kehoe, 2014), and human capital (Groysberg & Lee, 2009; Kehoe el., 2016) while extending enhancing scholarship in two important ways. First, we contribute to the literature on star performers identifying temporal considerations as an important, lifecycle-phase-based condition that dictates the manner in which and the degree to which star systems impact innovation outcomes. Our framework moves existing attempts to frame human capital resources as a 'war for talent' (Minbaeva & Collings, 2013; Somaya & Williamson, 2011). While extending the research on the prominence of stars, we develop a vital set of caveats that lend more nuanced understanding and assessment of star impacts. Through this, we identify inhibitors and facilitators of stars' impact as they vary across the arc of the star—firm relationship.

Our second key contribution extends the literature on innovation by situating the role of individuals, teams, and firms in multi-level fashion as they pursue explorative or exploitative innovation. Existing work on star scientists (e.g., Elfenbein & Sterling, 2018) correctly notes the heterogeneity of innovative outcomes as a function of stellar performance by key individuals, but the absence of clear differentiation between explorative and exploitative aims unwittingly conflates two dramatically different innovation contexts; contexts in which the role of star scientists is quite distinct, as are the outcomes. When firms pursue incremental or novel innovation (Hunt, 2013; Sathe, 1989), they might inadvertently endanger such efforts by high reliance on star system not under the right conditions. We propose that the attempt to attract stars is not necessary for all kinds of innovation endeavors. Our approach instead emphasizes the structures, path dependencies, and social mechanisms that influence how stars impact firms' innovative initiatives. In this fashion, we shed new light on how firms should focus on stars with the "best strategic fit" (Elfenbein & Sterling, 2018: 672) and with attentiveness to firm goals, rather than focusing on trying to win the war for talent through hiring stars in blanket fashion. Our contingency framework provides the necessary boundary conditions and sheds light on how stars impact organizational level outcomes. It also develops a more solid framework for developing, implementing, and evaluating innovative endeavors, offering researchers useful new insights.

Implications for Management

For managers, there is a clear message that firms should take a strategic approach to engaging stars throughout the employment lifecycle. Star systems -- to the extent that they are constructed under the realization that stars can sometimes create as many problems as they solve – may be viable, but managers could find themselves walking on a slippery slope. As our framework propounds, important contingencies should be considered in assessing the evolving contexts of a firm's innovation aims and the likely impact of a star performer in each specified context. This complex set of tradeoffs is particularly important in a knowledge economy wherein chief executive officers (CEOs) of top firms often cite the recruitment and retention of top talent as the leading constraint on innovation and business growth. For instance, as Mark Zuckerberg, CEO of Facebook, put it "[s]omeone who is exceptional in their role is not just a little better than someone who is pretty good…they are 100 times better" (Taylor, 2011). Meanwhile, Jeff Bezos, CEO of Amazon, broke ground on an expensive second headquarters on the East coast of the U.S. primarily in order to gain better access to tech stars of the future.

In light of these rather dramatic statements and investments from towering figures in the business world, a cautionary approach to star performers would seem to be swimming upstream. In fact, however, many facets of stars are neither well-understood nor deeply considered. While our framework does not dispute the indispensable and often irreplaceable contribution of star performers, we do think that there is ample reason for managers to press the "pause button" on expanding star systems as the antidote for sustainable competitive advantage. Our theoretical framework shows that it is important for managers to consider stars' impact by taking into account both their high performance (O'Boyle & Kroska, 2017) and their counterproductive impacts (Prado & Ferraro, 2018). Although stars have unique abilities which are likely to facilitate firms' innovation processes and outcomes, there are also social-structural impediments caused by the star systems. Managers often engage in the war for talent without considering their firms' current routines and structures and the attendant impact of status asymmetries on the social fabric of the firm. Insubstantial consideration is given to the temporal and contextual conditions that are likely to impact a star's effectiveness and his/her effects on the broader organization.

Conclusion

Our framework suggests that star performers are not uniformly beneficial to all firms under all conditions. It also emphasizes the importance of SHRM and talent management to hire and retain the right employees at the right time; specifically, when stars' presence aligns with firms' goals. Sloan and colleagues (2003: 236) underscore this point, noting that the key challenge in a knowledge economy, focused on human capital, involves "managing leadership talent strategically, to put the right person in the right place at the right time." Alert to this imperative, our framework is the first to account simultaneously for contextual and temporal dependencies regarding the impact of stars. Ironically, organizations that seek value-enhancing innovation through a singular reliance on star systems may inadvertently vitiate precisely the processes and outcomes that they hope to promote. Stated cosmologically: Stars often burn bright, providing vital illumination, energy, and planetary balance; but stars can also collapse into black holes. When they do, the gravitational pull places managerial attention, organizational resources, and firm-level goals at risk.

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Table 4-1 Management Literature on Star Performers and Star Systems

Focus/contribution of research	Author	Industry/ Context	Star definition	Research question	Finding
Emphasizing on productivity stars' impact	Aguinis & O'Boyle (2014)	NBA data	"a few individuals who contribute a disproportionate amount of output" (p. 313)	How stars impact individual, team and firm performance?	Stars are so rare and their impact is best described as a power law distribution.
	Aguinis, O'Boyle, Gonzalez-Mul´E, & Joo, 2016)	Multiple industries	High productivity	What impacts presence of smaller or bigger proportion of stars?	More multiplicity of productivity is likely to positively impact probability of a power law distribution of high productivity stars
Bringing nuance to conceptualizing stars and their impact	Kehoe, Lepak, & Bentley (2016)	Conceptual	- Universal star (individuals with high task performance and great external status) - Status star (individuals with broad external status) - Performance star (individuals with high task performance)	How do different kinds of stars impact value creation, value capture, and value preservation?	Status and universal stars are likely to capture more value in comparison to performance stars (relative to their value creation)
	Tzabbar (2009)	Biotechnology	Not provided	When recruitment of new scientists impact technological repositioning of firms?	Reliance of firms on incumbent star scientists makes it unlikely that firms make technological repositioning by recruiting scientists.
	Grigoriou & Rothaermel (2013)	Pharmaceutical firms	Relational stars: individuals embedded in social networks who are outliers in centrality or bridging behavior	How do relational stars impact firm innovation outcome?	Relational stars positively impact firm level outcomes
	Tzabbar & Kehoe (2013)	Biotechnology	Highly productive individuals	How does a star's departure impact firm innovation processes?	Stars' departure positively impacts exploration and negatively impacts exploitation
	Groysberg, Lee, & Nanda (2008); Groysberg & Lee (2009)	Security analyst	"disproportionately productive and valuable" (Lee et al., 2008, P. 1213)	How does performance of stars change after they change their employers?	Stars' performance declines after they switch to lesser or equal capable employer. Stars experience a short term decline on exploitative activities and long term decline on explorative activities after they are hired.
	Agrawal, McHale, & Oettl (2017)	University	Highly productive	How do hiring stars impact incumbents and joiners, and organizational performance?	Hiring stars have positive impact on the quality of subsequent scientists who join the firm.

Counterproductive impact of stars	Asgari & Hunt (2015)	Service industry	Highly productive with high visibility in the market	Does star system result in crowding out of value adding contributions of non-stars?	As firms lose star employees, they suffer less decline in their performance in comparison to losing non-stars.
	Prato & Ferraro (2018)	Securities analysts	Individuals with high status	How does hiring new stars impact incumbent employees' performance?	Hiring star performers negatively impacts firms' incumbents' performance
	Chen & Garg (2018)	NBA	Individuals who "make disproportionate individual contributions to their organizations" (p. 1240)	How do stars' absence impact organizational performance?	Stars' absence positively impact organizational performance
	Kehoe & Tzabbar (2015)	Biotechnology	Individuals who are greatly productive and have high visibility in the industry	How do stars impact firm innovation performance of firms?	Presence of stars limits the emergence of other innovative leaders in firms.
	Oldroyd & Morris (2012)	Conceptual	Individuals with high performance and high visibility	How does stardom impact stars and firm performance?	Abundant social capital of stars is likely to increase information overload, negatively impacts stars' performance, information sharing, turnover and consequently firm performance due.

Table 4-2 Facilitators, Inhibitors and Mechanisms of Stars' Impact on Firms' Innovation Outcomes

Onboarding		**How stars (are expected to) positively impact firm outcomes?**	**What limits stars' ability to positively impact firm outcomes?**	**What facilitates stars' ability to positively impact firm outcomes?**	**How stars negatively impact firm outcomes?**	**Propositions**
	Exploration	Unique knowledge and expertise especially in unrelated and distant knowledge domains Develop knowledge search routines to explore new knowledge domains Knowledge spillover Network resources	Existing structures and routines of firms Low motivation to interact and share knowledge Slow accumulation of complex resources	NA	NA	***Proposition 1:*** *Onboarding a star scientist is likely to incrementally increase a firms' exploration outcomes.*
	Exploitation	Use their knowledge and expertise to exploit current knowledge domains	Path-dependent nature of exploitation	NA	Disruptions and shocks to current knowledge sharing routines and absorptive processes	***Proposition 2:*** *Onboarding a star scientist is likely to negatively impact firms' exploitation outcome.*
Embedded	**Exploration**	Unique knowledge and expertise especially in unrelated and distant knowledge domains Develop knowledge search routines to explore new knowledge domains Knowledge spillover Network resources	NA	Ability to deal with uncertainty Unique search and problem solving behavior Control over resources	NA	***Proposition 3.*** *A star's embedded presence is likely to substantially increase the exploration outcomes of firms.*

	Exploitation	Use their knowledge and expertise to exploit current knowledge domains	NA	Increasing firms' knowledge base	Disruptions to current knowledge sharing routines Power imbalance	***Proposition 4:*** *A star's embedded presence is likely to modestly increase the exploitation outcomes of firms.*
Departure	**Exploration**	NA	NA	NA	Loss of unique knowledge and expertise to explore new knowledge domains Loss of stars abilities to develop new search routines which are star-centric Loss of stars' network resources	***Proposition 5.*** *The departure of a star is likely to greatly decrease a firm's exploration outcomes.*
	Exploitation	Reduced power imbalance and availability of resources to other scientists to exploit current knowledge domains Reduced status asymmetry and more efficient knowledge exchange	NA	NA	Loss of their knowledge and expertise to exploit current knowledge domains	***Proposition 6:*** *The departure of a star is likely to incrementally increase a firm's exploitation outcomes.*

Figure 4-1 Proposed Conditions of the Contingency Framework

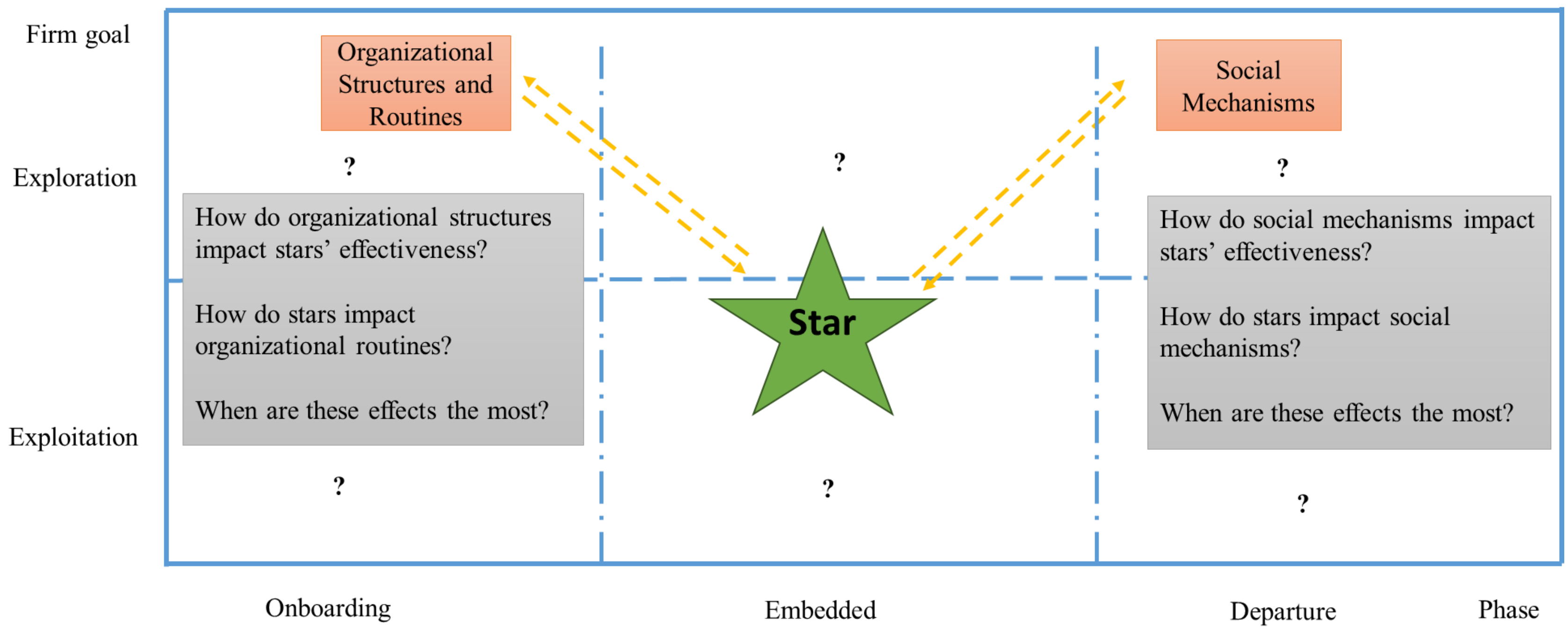

Figure 4-2 Summary of Propositions on How Stars Impact Firms Innovation

Onboarding

Exploration (+)
Proposition 1: *Onboarding a star scientist is likely to incrementally increase a firms' exploration outcomes.*

Exploitation (-)
Proposition 2: *Onboarding a star scientist is likely to negatively impact firms' exploitation outcome.*

Embedded

Exploration (+++)
Proposition 3. *A star's embedded presence is likely to substantially increase the exploration outcomes of firms.*

Exploitation (++)
Proposition 4: *A star's embedded presence is likely to modestly increase the exploitation outcomes of firms.*

Departure

Exploration (- -)
Proposition 5. *The departure of a star is likely to greatly decrease a firm's exploration outcomes.*

Exploitation (+)
Proposition 6: *The departure of a star is likely to incrementally increase a firm's exploitation outcomes.*

CHAPTER 5: CONTRIBUTIONS AND IMPLICATIONS

Across the three papers of my dissertation, I explained the multi-level processes of innovation generation and innovation selection. I examined how unique knowledge types impact innovation at both the firm level and the industry level. I used the emerging high technology context of small satellites industry to test my hypotheses of Paper One and Paper Two. In Paper One, I adopted a supply-demand perspective (Priem, Li, & Carr, 2012), and theorized how suppliers of technology possessing unique scientific and technological knowledge, and users of technology possessing knowledge of demand contribute to innovation. I focused on two key aspects of innovation: innovation generation (novelty and breadth), and innovation selection (coherence). Each of these aspects is important in the emergence and evolution of industries: novelty of innovation is the main driver of change (Kaplan & Vakili, 2015) and the emergence of industries; breadth of innovation shows diversity of solution sets (Brown & Eisenhardt, 1995) and is important in the maturity of industries; and coherence shows the level of agreement and convergence on technologies and is the main driver of commercialization (Suarez, Grodal, & Gotsopoulos, 2015) and the growth of industries. Results showed that the contribution of suppliers and users of technology differs according to each aspect of innovation, and their contribution is likely to vary over the industry lifecycle.

In Paper Two, with a focus on the firm level innovation, I investigated how different types of knowledge possessed by the main drivers of innovation—CEOs and scientists (Cho & Kim, 2017; Park & Tzabbar, 2016; Subramanian, Lim, & Soh, 2013)—impact firms' generation of novel innovation. In an attempt to address science-business tensions in firms (Christensen, 1997), I theorized how an understudied aspect of scientists' knowledge—i.e., scientists' business knowledge—and an understudied aspect of CEOs' knowledge—i.e., CEOs' scientific knowledge—impact firm novel innovation. Results suggested that CEOs' scientific knowledge enhances the probability of pursuing novelty, and this impact is higher when scientists do not have business knowledge. Interestingly, the probability of pursuing novel innovation is higher when the knowledge gap between scientists and CEOs is filled with CEOs' scientific knowledge, and not when it is filled with both CEOs' scientific knowledge and scientists' business knowledge.

In Paper Three, I explained how scientists who have high levels of scientific and technological knowledge and provide value-enhancing contributions—i.e., star scientists—impact firm level innovation generation and selection (Aguinis & O'Boyle, 2014; Groysberg & Lee, 2009). Although there is great emphasis on the notion that stars are indispensable to firms' performance (Boynton & Fischer, 2005; Wright, Coff, & Molierno, 2014), recent scholarly works pointed out to the counterproductive impacts of stars (e.g., Asgari & Hunt, 2015; Kehoe & Tzabbar 2015). Taking a contingency approach, I built theory on the mechanisms through which stars impact firm level outcomes and connected human resources management to strategy and innovation literature. I integrated organization-level contingencies – related to the role of a star for innovation generation (i.e., exploration) or innovation selection (i.e., exploitation) – and employee-level contingencies – related to a star's stage of employment – to explore how and if stars promote and inhibit organizational impact.

Overall, my dissertation improved understanding of the multi-level mechanisms of innovation generation and innovation selection, theorizing about the tensions and complementarities between unique knowledge types: business knowledge and scientific knowledge at the firm level, and technological knowledge and user knowledge at the industry level. I illuminated how the impact of unique types of knowledge on innovation generation and innovation selection varies based on multiple contingencies, including the organizational roles of the individuals who possess the knowledge, the industry life cycle, and the evolving nature of the relationship between employees and employers. My dissertation thus creates a basis for future scholars to theorize and examine complementarities and tensions among different knowledge types in a more systematic manner.

Contribution

My dissertation makes a number of important contributions. Table 5-1 summarizes the contributions and future research implications of the dissertation.

[Insert Table 5-1 about here]

First, my research contributes to the literature on industry evolution by uniquely incorporating demand-side perspective to the supply-oriented literature on industry evolution. It theorizes how users and suppliers of technology contribute to distinct aspects of innovation generation and innovation selection over the industry life cycle. It provides empirical evidence on the importance and uniqueness of contributions of users to distinct aspects of innovation generation and selection. My findings suggest that demand and supply make distinct contributions to innovation at different stages of industry life cycle, thereby shedding light on the role of users and suppliers in industry emergence and evolution.

Second, my dissertation contributes to the innovation literature by theorizing about the unique aspects of innovation generation and innovation selection, and theoretically mapping them at the firm level and the industry level. At the industry level, I identify novelty, breadth, and coherence of innovation as unique aspects of innovation generation and innovation selection that contribute to industry emergence and evolution. Empirical evidence suggests that the knowledge of suppliers and users makes unique contributions to each aspect of innovation generation and selection. At the firm level, I theorize how innovation generation and innovation selection are pursued in firms. I explain how the business and scientific knowledge of CEOs and scientists helps firms to overcome science-business tension in their pursuit of novelty. My results suggest that CEOs' scientific knowledge is an important driver of firms' generation of novel innovation, and this impact is higher when scientists do not have business knowledge. Additionally, I reveal that how the knowledge gap between scientists and CEOs is filled has important implications on firms' novel pursuits.

Third, my research theoretically grounds limits and boundaries regarding how star scientists who possess high levels of scientific and technological knowledge impact firms' generation and selection of innovation. I theorize how the life cycle of employees reflects evolving relationships between employees and employers and acts as an important indicator of stars' impact on firms-level innovation generation and selection; thereby bridging the human resource management and strategy and innovation literatures. My research provides boundary conditions that govern the favorable and unfavorable impact of stars, while advancing a theory of "non-uniformity," a predictive basis that accounts for changes in the organization-star relationship over time and models stars' impact as a function of the manner in which organizations pursue innovation.

Fourth, in addition to theoretical and empirical contributions, my research makes important methodological contributions. It shows how machine learning and text analytic techniques can be used in the strategy field to address questions that requires analysis of big or textual data. I developed new measures of innovation, showing the possibility of developing unique applications of such techniques. Also, it shows how varied sources of data can be used in order to examine contexts that lack established sources of data (e.g., emerging contexts). I showed how textual content of grants and papers can be used to examine innovation generation and selection in emerging high technology industries. My application of unique data sources extends the boundaries of common approaches to data collection and analysis in the strategy and innovation literature.

Future Research Implications

My dissertation provides several opportunities for future research on industry evolution. First, future research can conceptually distinguish among entrepreneurial ventures, established firms, and research institutes on the demand side of the industry. This is particularly important as each of these sources of knowledge has unique institutional settings, knowledge bases and capabilities (McKendrick, Jaffee, Carroll, & Khessina, 2003; Sauermann & Stephan, 2013; York & Lenox, 2013). As a result, further examination of different aspects of user knowledge is likely to bring a deeper understanding on how users contribute to innovation. Second, future research can further distinguish between consumers (as end users), and customers (as intermediary firms) (Priem et al., 2012) and how they contribute to unique aspects of innovation over the industry life cycle. Literature suggests that there is distinction between users, lead users, and customers (Danneels, 2003). However, this level of precision has not been incorporated in the industry evolution literature. Thus, in-depth classification of actors on the demand side of the industry would provide more clarity on how demand contributes to innovation generation and selection.

Third, my dissertation shows fruitful directions for future research in innovation. Although I did not distinguish between scientific—i.e., fundamental knowledge—and technological knowledge—i.e., applied knowledge (Murray & Stern, 2007; Stokes, 1997), future research can further distinguish how these types of knowledge impact firms' novel pursuits. There is a clear distinction between scientific and technological knowledge in terms of their applicability and nature and how each contributes to innovation (e.g., Baba, Shichijo, & Sedita, 2009).

Distinguishing between these types of knowledge is likely to provide insights on how firms overcome tensions among misaligned goals in their pursuit of novelty.

Fourth, future scholars can further examine how specific kinds of knowledge possessed by organization members other than CEOs and scientists might impact innovation generation. For instance, researchers can examine how unique knowledge types of middle managers or top management teams impact firms' pursuit of innovation. Some research shows that interactions between middle managers and upper echelons is important in how firms pursue innovation (Heyden, Sidhu, & Volberda, 2018), which suggests it is likely that multilevel interactions among CEOs, middle managers, and scientists have important implications on how firms address business-science tensions and pursue innovation. Fifth, researchers can identify further boundary conditions on how stars impact innovation generation, for instance, they can differentiate between scientists who become stars in firms, and those who are hired. Research suggests that social mechanisms that constitute stars' relationships with other scientists have important implications on stars' performance (Call, Nyberg, & Thatcher, 2015; Groysberg & Lee, 2009), suggesting that star scientists who are hired have different impacts from those nurtured within firms.

Finally, I suggest that scholars could benefit from novel data sources and advanced text analysis and machine learning techniques. Future research can use such novel techniques to address questions especially in earlier stages of the emergence of industries that lack established data sources. Scholars can benefit from such methods to analyze big data sources, while collective use of multiple data sources, and especially their textual contents, can also lead to new measures for variables of interest.

Conclusion

Overall, my dissertation theorized and examined multi-level mechanisms of innovation generation and selection at both the firm level and the industry level. I employed a novel empirical context—small satellites as a high technology emerging industry—to test the hypotheses of Paper One and Paper Two. This emerging high technology industry with nascent stage firms provided a great context for my research. At the industry level, I theorized that distinct knowledge types of suppliers and users of technology make unique contributions to different aspects of innovation and play important roles at different stages of the industry. At the firm level, I examined business-science tensions in firms' pursuit of novelty and explained that how the knowledge gap between scientists and CEOs – as two main drivers of innovation – is filled has important implications on firms' pursuit of novelty. Additionally, I illuminated trade-offs in how high performing employees impact innovation generation and selection, and clarified that that the impact of star scientists may extend beyond their valuable knowledge.

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Table 5-1 Summary of Contributions and Future Research Implications

Literature Stream	Contributions	Future Research Implications
Innovation	**Theoretical** • Identifies unique aspects of innovation generation and innovation selection, and theoretically maps them at the firm and the industry level • Provides new explanations on how firms overcome business-science tensions to pursue novelty emphasizing on interactions between CEOs and scientists • Theorizes on the boundary conditions on how star scientists impact innovation generation identifying evolving relationships between employees and employers as an important determinant of innovation **Empirical** • Provides empirical evidence that knowledge of suppliers and users makes unique contributions to each aspect of innovation generation and selection • Shows that CEOs' scientific knowledge is an important driver of firms' novel innovation generation, and that it is not only important to fill the knowledge gap between scientists and CEOs, but also how the knowledge gap is filled	• Future scholars can further examine how specific kinds of knowledge possessed by varied organizational roles could impact innovation generation • Researchers can identify further boundary conditions on how stars impact innovation generation; for instance, they can differentiate between scientists who become stars in firms, or those who are hired

Industry Evolution	**Theoretical** • Uniquely brings demand-side perspective to the heavily supply-side oriented literature • Theoretically conceptualizes how users contribute to industry emergence and evolution over the industry life cycle **Empirical** • Illustrates how users and suppliers of technology make unique contributions to different aspects of innovation (i.e., novelty, breadth, and coherence), and consequently industry emergence and evolution • Shows how contribution of technology push and demand pull varies over the life cycle of an industry	• Future research can further distinguish between consumers (as end users) and customers (as intermediary firms) and examine how they contribute to innovation over the industry life cycle • Future research can further conceptually distinguish among actors in industries such as research institutes, entrepreneurial ventures, and established firms on demand and supply side of industries
Methodology	• Shows the possibility of using novel methodologies such as text analysis and machine learning techniques to analyze big data or study emerging contexts • Illustrates the possibility of using novel datasets such as textual documents of papers as useful sources of data	• Future research can use novel techniques to address questions in earlier stages of the emergence of industries that lack established data sources • Future scholars can collectively use multiple data sources such as patents, papers, and grants in order to develop new measures of innovation