The Role of Firm Capability, Managerial Cognition, and Ecosystem on Innovation: Investigation of The Satellite Industry

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ACADEMIC ABSTRACT

In this dissertation, I systematically explore the nature and role of two firm capabilities: absorptive capacity (or external learning capability) and technological capability. I examine how firm capability interacts with intra-firm and industry factors, and how it impacts organizational outcomes. In the first paper, I review literature on absorptive capacity and distill its distinct effect on various organizational outcomes. I identify key theoretical underpinnings behind the diverse conceptualizations of absorptive capacity and their corresponding measures, and use meta-analytical techniques to synthesize the effects of absorptive capacity. The second and third paper of my dissertation examine how technological capability interacts with certain internal and external contingency factors in influencing firm innovation and industry evolution. In the second paper, I take an intra-firm focus, and I identify managerial cognition as an important internal factor that impacts the relationship between technological capability and innovation. More specifically, I study how a firm’s technological competence interacts with managerial experience in shaping that firm’s innovation choices. Using data from the satellite industry, I show that diversity and relatedness of technological resource, as well as CEO experience, work differently in shaping product versus application innovations. In the third paper, I investigate how capabilities beyond focal technology producers influence industry evolution. Based on longitudinal analyses of the evolution of the satellite industry, I show that complementors, component suppliers, and customers are important external factors that shape industry evolution. Overall, my dissertation demonstrates the interrelated roles of firm capability, managerial cognition, and innovation ecosystem on firm and industry-level outcomes.
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GENERAL AUDIENCE ABSTRACT

In this dissertation, I examine how firm capability interacts with other factors in influencing companies’ innovation decisions and the evolution of an industry. In the first paper, I review and synthesize existing studies on firm capability by focusing on the absorptive capacity (AC) literature. I identify key conceptualizations of AC, key outcomes of AC, and use meta-analytic techniques to distill AC’s effects. In the second paper, I examine how technological capability works together with managerial experience in shaping companies’ innovation choices in the small satellite industry. Small satellites, commonly defined as satellites that are less than 500 kilograms, are important innovations that substantially reduced the costs of building, launching, and operating satellites. In recent years, the small satellite industry has seen tremendous growth in terms of satellite production and deployment. I categorize innovation choices in this industry as product innovation (such as introduction of new launch systems, improved satellite components, and novel ground equipment) or application innovation (such as finding novel applications of existing satellite products by analyzing data transmitted from satellite systems and providing implications). Results show that while having related technology is positively related to product innovation, having a CEO with more diverse experience is positively related to application innovation. In the third paper, I examine how the small satellite industry emerged and evolved. Results show that beyond technological capabilities of focal small satellite manufacturers, technological advancements from complementors (launch vehicle providers) and customers (satellite operators) have jointly influenced the evolution of this industry.
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CHAPTER 1: INTRODUCTION

Firm capability is one of the most studied constructs in the field of strategic management (Arora & Gambardella, 1994; Cohen & Levinthal, 1990; Coombs & Bierly, 2006; Zhou & Wu, 2010). Scholars have examined many aspects of firm capability, such as dynamic capabilities (Eisenhardt & Martin, 2000; Teece, Pisano & Shuen, 1997), combinative capabilities (Kogut & Zander, 1992), technological capabilities (Stuart & Podolny, 1996; Zhou & Wu, 2010), and learning capabilities (Cohen & Levinthal, 1990; Kale & Singh, 2007). Studies have shown that firm capability influences a wide range of outcomes including learning (Lane & Lubatkin, 1998; Schildt, Keil & Maula, 2012), innovation (Alegre & Chiva, 2008; Rothaermel & Hess, 2007), firm performance (Calantone, Cavusgil & Zhao, 2002; Zaheer & Bell, 2005), and industry evolution (Klepper, 2002; Levinthal & Myatt, 1994). In this dissertation, I focus on two aspects of firm capability: learning capability and technological capability.

As firms increasingly rely on external sources of knowledge (Cohen & Levinthal, 1990; Powell, Koput & SmithDoerr, 1996), a firm’s ability to leverage external knowledge is critical for its growth and success (Fey, 2005; Wadhwa & Kotha, 2006). Accordingly, the first paper of my dissertation focuses on such learning capability, commonly conceptualized as absorptive capacity.

Absorptive capacity (AC) refers to a firm’s ability to “recognize the value of new, external information, assimilate, and apply it to commercial ends” (Cohen and Levinthal, 1990: 128). AC explanations are used to examine how a firm’s internal capability influences its leveraging of new external knowledge (Volberda, Foss & Lyles, 2010). While the rapid growth in the AC literature (Volberda et al., 2010; Zahra & George, 2002b) underscores the importance of AC, the literature is rather fragmented. Often, researchers use the same foundational
definition of Cohen and Levinthal, but conceptualize and measure AC very differently. The core of AC as a firm’s internal capability to leverage external knowledge is getting lost. Scholars have very “diverse” (Zahra & George, 2002a) and “fractioned” views (Volberda et al., 2010) on what constitutes AC. It is also unclear how different aspects of AC have different impacts on various organizational outcomes. In the first paper, through a systematic review of the literature, I identify three core aspects of AC—effort, competence, and process—and three important outcomes—knowledge generation, innovation generation, and firm performance. I then perform meta-analyses to distill empirical findings and highlight key areas where AC matters the most. Results show that AC matters most for innovation outcomes, and the process aspect of AC has the strongest effect across all firm-level outcomes. This paper provides conceptual clarity on the core of AC, distills empirical evidence on the role of AC on firm outcomes, and articulates the theoretical mechanisms shaping the AC-outcome relationship.

Findings from the first paper provide several implications and motivate my second and third paper. First, results show that AC is most useful in predicting innovation outcomes. While the main effect of AC on innovation is very strong, the effect size becomes much smaller after controlling for the other factors that matter together with AC, such as internal use of resources and external environmental conditions. The sharp decrease in effect sizes indicates the importance of considering these contingencies when examining the impact of AC or more broadly the impact of any firm capability. Second, the strongest effect of the process aspect of AC implies the important role of managers. Routines and processes are often viewed as capability building blocks (Eggers & Kaplan, 2013), and managers play central roles in selecting, implementing and monitoring which organizational routines get developed into capabilities (Bantel & Jackson, 1989; Barker & Mueller, 2002; Eggers & Kaplan, 2013). I build
on this core idea and explore the interplay between firm capability and managerial cognition in the second paper. Lastly, when predicting innovation outcomes, the competence aspect of AC provides the strongest effect size. Therefore, in my second and third papers, where innovation is the key outcome of interest, I focus on the technological competence aspect of firm capability.

Building on these insights, the second and third papers examine how firm capability interacts with other intra-firm and industry factors in influencing innovation. In the second paper, I take an intra-firm focus, and identify managerial cognition as an important internal factor that moderates the relationship between firm capability and innovation outcomes. Managerial cognition and organizational capability are reciprocally intertwined (Eggers & Kaplan, 2013): managers influence the selection of experiences that could be developed into capability building blocks. Managers also interpret firm capabilities and identify their purposes and usages (Benner & Tripsas, 2012; Eggers & Kaplan, 2013; Gavetti, 2012). Despite the imperative role of managers, the capability literature has paid less attention to the cognition of managers. Some studies have used capability to infer managerial cognition (Ahuja & Lampert, 2001), but very few have explicitly studied how managerial cognition and firm capability work together in influencing firms’ innovation decisions.

Therefore, in the second paper, I integrate the literature on technological competence (Danneels, 2007; Miller, 2006; Sampson, 2007) with literature on managerial cognition (Carpenter, Geletkanycz & Sanders, 2004; Hambrick, 2007; Hambrick & Fukutomi, 1991). More specifically, I focus on a commonly used proxy for managerial cognition – CEO experience. Using the small satellite industry as my research context, I explore how technological competence and CEO experience interactively shape firms’ innovation choices. I identify product and application innovations as two prominent innovation choices. I further
theorize that diversity and relatedness of technological competence, as well as CEO experience work differently in shaping product versus application innovations. Results based on data from the small satellites industry show that while firms with related technologies are more likely to pursue product innovations, this effect becomes insignificant when their CEOs have more diverse industry experience. On the other hand, firms with more diverse technologies are more likely to pursue application innovations, but this likelihood is reduced for firms that have CEOs with more related industry experience. Paper Two contributes to the literature by explaining the unique roles of technological capability and CEOs in influencing innovation choices in an emerging industry context and by integrating insights from previously separated literature streams on capability and cognition.

Paper Three has an industry-centric focus and investigates how capabilities beyond the focal firm could impact the evolution of an industry. Building on the literature on industry lifecycle (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Klepper, 1997) and innovation ecosystem (Adner & Kapoor, 2016; Henderson, 1995), I theorize that a multitude of actors in the innovation ecosystem, including focal technology producers, complementors, component providers, and customers, collectively shape industry evolution. I then provide illustrative data from the satellite industry to show that traditional industry evolution models are possibly inadequate to explain the emergence and growth of new technology-intensive industries such as the satellite industry. I show that even though large satellites had superior performance compared to small satellites, large satellite were not dominant in the beginning of the satellite history. Further, while satellite manufacturers had developed capabilities to produce modern small satellites since 1986, small satellite technologies did not become widely used until 2012. These findings contradict the commonly held notions that focal technology producers are
the main contributors of industry evolution and adoption of new technologies. My investigation of the evolution of the satellite industry reveals that value creation from satellite manufacturers (focal technology producers) launch vehicle providers (complementors), satellite subsystem suppliers (component suppliers), and satellite operators (customers) are highly interdependent. While each actor provides unique values, actors also need to collaborate with each other and combine their individual offerings into a coherent solution. These findings suggest that an ecosystem perspective is necessary to explain the evolutions of technology-intensive industries.

[Insert Figure 1-1 about here]

Taken together, this dissertation systematically explores the nature and role of two firm capabilities: absorptive capacity (or external learning capability) and technological capability. It examines how firm capability interacts with intra-firm and industry factors, and how it impacts organizational outcomes. Figure 1-1 provides an illustration of the overall conceptual model and the focus of each research paper. With a focus on AC as a critical learning capability, Paper One contributes to the literature by underscoring the core of the AC literature and by distilling and synthesizing existing findings on the relationship between AC and organizational outcomes. The findings help develop a cumulative knowledge on AC and shape future research agenda. Paper Two contributes to the literature by providing empirical evidence on the role of a firm’s technological competence and CEO cognition and how these two separately and jointly influence the firm’s innovation choices. It also provides a basis for more in-depth future studies on the interplay. Paper Three further examines the capability-cognition interplay with a focus on the innovation ecosystem and the critical roles of each actor in the innovation ecosystem. The conceptual insights developed and illustrative data provided on Paper Three show that a multitude of actors play unique roles in the evolution of an emerging industry and thus question
the commonly held view on industry evolution that the focal technology providers are the primary drivers of industry change. More broadly, my dissertation shows that the effect of firm capability varies depending on the aspects measured and outcomes examined. Within a firm, the influence of organizational capability is dependent on managerial cognition. Within an industry, the impact of firm capability is contingent upon other actors in the ecosystem. This dissertation thus provides unique insights on the interrelated roles of firm capability, managerial cognition, and innovation ecosystem for firm innovation and industry evolution.
REFERENCES


Figure 1-1 Illustration of the Overall Conceptual Model and the Focus of Each Research Paper

**Paper One: Main Relationship**

*Intra-Firm Focus with Inter-firm Interface*

**Internal Capability:**
- Absorptive Capacity
  - Effort
  - Competence
  - Process

**Organizational Outcomes:**
- Knowledge Generation
- Innovation Generation
- Firm Performance

**Overall Conceptual Model:**

**Internal Capability**

**Organizational and Industry Level Outcomes**

**Internal and External Contingency Factors**

**Paper Two: Internal Contingency**

*Intra-Firm Focus*

**Internal Capability:**
- Technological Competence

**Organizational Outcome:**
- Innovation Choice

**Internal Contingency Factor:**
- Managerial Cognition

**Paper Three: External Contingency**

*Industry Focus*

**Internal Capability:**
- Collective Capability of Technology Producers

**Industry Level Outcome:**
- Industry Evolution

**External Contingency Factor:**
- Other Actors in the Innovation Ecosystem
CHAPTER 2 : PAPER ONE

THE CORE OF ABSORPTIVE CAPACITY: A SYNTHESIS OF THE LITERATURE AND CONSOLIDATION OF FINDINGS

2.1 INTRODUCTION

Absorptive capacity (AC), defined as a firm’s ability to “recognize the value of new, external information, assimilate it, and apply it to commercial ends” (Cohen & Levinthal, 1990: 128), is one of the most widely studied concepts in strategic management. A keyword search using the EBSCO Business Source Complete database for the years 1990–2016 yielded 1,141 published papers with “absorptive capacity” in the title, abstract or keywords. Multiple attempts to clarify, review, and at times redefine AC (Lane, Koka, & Pathak, 2006; Todorova & Durisin, 2007; Volberda, Foss, & Lyles, 2010; Zahra & George, 2002) are also indicative of the importance of the concept.

Our review of the literature shows three critical issues. First, the core of AC as a firm’s internal ability to acquire and apply external knowledge as originally articulated by Cohen and Levinthal (1990) is getting lost as “fractioned” views have developed on the topic (Lane et al., 2006; Volberda et al., 2010). More than 30 different measurements of AC have been used, leading to fragmentation and confusion regarding what constitutes AC and how to measure it. Second, the boundaries between AC and its outcomes have become blurred. Sometimes the same measures (such as R&D investment or patent counts) have been used both as an indicator of AC (e.g., de Faria, Lima, & Santos, 2010; Grimpe & Sofka, 2009; Tsai, 2001) and as an outcome of AC (Arbussà & Coenders, 2007; Nambisan, 2013; Phene, Fladmoe-Lindquist, & Marsh, 2006). The causal mechanisms through which AC influences outcomes are also unclear. The blurred

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1 This paper was developed in collaboration with Dr. Devi Gnyawali, Dr. Manish Srivastava, and Elham Asgari
boundary and causal ambiguity have led to theoretical confusion and limited research rigor. Finally and most importantly, it is unclear what the literature stream has accomplished because limited efforts are made to synthesize the literature and develop a cumulative body of knowledge. Little is known about what the most commonly studied aspects of AC are and to what extent those aspects matter for different outcomes.

With a focus on the original conceptualization of AC as internal ability for leveraging external knowledge, we address the abovementioned issues in several ways. First, we systematically review the conceptual and empirical literature on AC and distill key insights on the core aspects of AC and its outcomes. Our review and distillation of the literature led us to identify three core aspects of AC—effort, competence, and process—for leveraging external knowledge. We also identify three outcomes: knowledge generation, innovation generation, and firm performance. This conceptual streamlining distinguishes AC from outcomes and provides a basis for consolidation of empirical findings in the literature. Second, we synthesize and distill empirical findings on AC and its role through meta-analysis. Our meta-analysis shows that AC has a strong positive effect on firm outcomes. We also find that the effects of AC vary depending on the aspect of AC, outcome of AC, and their combinations. The process aspect has the strongest positive effect on the outcomes, the positive effect of AC is most pronounced for innovation generation, and the competence-innovation generation combination has the strongest positive effect. Third, with the core of AC distilled through the conceptual review and meta-analysis, we proceed to articulate causal mechanisms through which external learning effects of AC occur and theoretically connect such mechanisms to external knowledge characteristics.

Through our synthesis of the conceptual and empirical literature, identification of key aspects and outcomes of AC, and articulation of theoretical mechanisms on the core of AC, we
provide ways to improve both conceptual and empirical rigor (Suddaby, 2010) in AC research. Increased rigor and consistency in conceptualization and operationalization contributes to the development of a clearer and stronger theory of AC. Since a synthesis of the literature showing areas of clear research findings is a “critical first step in effective use of scientific evidence” (Rousseau, Manning, & Denyer, 2008: 476), our synthesis of empirical findings through meta-analysis serves as a very important step toward developing cumulative knowledge. Overall, our paper provides conceptual clarity on the core of AC, distills empirical evidence on the role of AC on firm outcomes, articulates underlying theoretical mechanisms shaping the AC-outcome relationship, and offers a more focused agenda for future research.

2.2 LITERATURE ON ABSORPTIVE CAPACITY

Over the past 27 years, multiple attempts have been made (Lane et al., 2006; Volberda et al., 2010; Zahra & George, 2002) to review and organize the AC literature, and each attempt has expanded the concept of AC and developed an organizing framework for the literature. We begin by reviewing the key conceptual and review papers on the topic of AC. We then synthesize the literature to identify the core of AC.

Cohen & Levinthal (1989, 1990)’s original conceptualization emphasized that AC is about the acquisition and utilization of external knowledge. They suggested that R&D investment not only helps to generate innovation internally, but also contributes to a firm's ability to assimilate and exploit knowledge from the external environment. This later role of R&D is what they call a firm's “absorptive capacity” (Cohen & Levinthal, 1989: 569). They further emphasized that AC is largely a function of the level of prior related knowledge. Having more prior related knowledge improves the firm’s ability to recognize and understand new outside information.
Since then, scholars have reconceptualized and extended the AC concept in several different ways. For example, Lane & Lubatkin (1998) underscored the externally-driven nature of AC and introduced the term relative AC. They suggested that in the context of a learning dyad (student-teacher) the ability of a firm to learn from another firm is jointly determined by the relative characteristics of the dyad. Zahra and George (2002) extended the concept by taking a process perspective and decomposed AC as potential versus realized AC. They argued that potential AC is about the firm’s receptivity to acquiring and assimilating external knowledge, and realized AC is about transformation and exploitation of the absorbed knowledge. Lewin, Massini, and Carine (2011) further built on the process perspective and proposed a routine-based model of AC. They suggested the need to examine organizational practices in order to understand and measure AC. Collectively, the literature has followed the initial point made by Cohen and Levinthal (1990) about the need for investing in technological development. More recently, the importance of organizational mechanisms has been emphasized.

Scholars have pointed out conceptual concerns with how the construct is viewed and used. Based on their analysis of the literature, Lane and colleagues (2006) argued that the concept of AC has become “reified”, i.e., original definition and assumption that underlie the construct have gradually eroded and AC is being used as a general-purpose construct. Volberda and colleagues (2010) conducted a bibliometric analysis of the literature and noted that the AC construct is “surrounded by considerable ambiguity with respect to its meaning and nature” (Volberda et al., 2010: 943). While Zahra and George (2002) stressed the importance of explicit processes for potential and realized AC, the “exploitation” aspect of realized AC has been used in other papers as an outcome of AC (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Nooteboom, Vanhaverbeke, Duysters, Gilsing, & van den Oord, 2007), leading to
an unclear boundary between AC and its outcomes. We observe that the attempts to redefine and expand AC have led to a sizeable growth in the literature, including new conceptualizations and measurements. We also find that the existence of more than 30 different measures of AC and the use of the same measure for AC and for outcome have led to further confusion regarding what AC is and what role it plays.

Given the growth and confusion in the literature, we believe that it is important to assess the current state of the literature, synthesize it, and streamline the conversation on the core of AC. Accordingly, our intent is not to do yet another review and develop an organizing framework. Instead, our focus is on taking a systematic look at the theoretical and empirical literature with a particular emphasis on two core aspects: (a) AC itself as a firm’s internal ability to leverage external knowledge, and (b) influence of AC on firm outcomes. We distill theoretical insights, synthesize empirical findings through meta-analysis, clarify the conceptual boundary between AC and outcomes, and develop a more focused agenda informed by the synthesis of the literature.

**Key Aspects of Absorptive Capacity: Effort, Competence, and Process**

As noted above, our focus is on AC as internal ability to leverage external knowledge. After a systematic look at the literature and distillation of conceptual insights and empirical findings, we identify three common aspects that cover the majority of the discussion of AC: effort, competence, and process. Table 2-1 provides a summary of these aspects with the measures used in the empirical literature to capture them.

[Insert Table 2-1 about here]

AC as *Effort* to acquire and use external knowledge is the most fundamental aspect of AC. We use the label “effort” in line with the original point made by Cohen & Levinthal (1990) who
argued that “intensity of effort is critical” (p. 131) and that if a firm wishes to develop AC, “then the firm must dedicate effort” (p. 150). In their subsequent study “Fortune Favors the Prepared Firm”, they once again stressed that for firms to use accessible external knowledge, they first need to spend time and devote energy to develop internal expertise (Cohen & Levinthal, 1994: 228). Other scholars have continued to emphasize the impotence of effort. Lenox & King (2004: 332) noted that “an agent searching for new knowledge must make an investment just to see what might be there”. Kim (1998: 507) also stressed that “exposure of a firm to relevant external knowledge is insufficient unless an effort is made to internalize it”.

Two sets of measures are generally used to capture effort: financial investment in R&D and commitments for technology development. R&D has been the most commonly used measure of effort as R&D conducted by private firms is an investment activity (Hall, Jaffe, & Trajtenberg, 2005) and creates potentials to discover new knowledge (Gunther, McGrath, & Nerkar, 2004). More R&D investments would mean that the firm has the potential to discover and build on relevant and useful external knowledge. Empirical measures of commitments for technology development include the number of R&D employees (Huang, Lin, Wu, & Yu, 2015), percentage of technological employees (Estrada, de la Fuente, & Martin-Cruz, 2010; Luo, 1997), and percentage of employees with the state of the art technological skills (Matusik & Heeley, 2005).

*Competence* is the second aspect of AC. It refers to a firm’s existing knowledge and expertise for acquiring and leveraging external knowledge. Researchers have mostly focused on technological competence in their empirical measures of AC. While effort generally reflects the potential, competence reflects existing ability. Competence or stock of prior knowledge is noted in Cohen and Levinthal’s statement that “the organization needs prior related knowledge to assimilate and use new knowledge” (1990: 129). Accumulated prior knowledge increases both
the ability to acquire new knowledge and the ability to recall and use it (Cohen & Levinthal, 1990; Kim, 1998).

A firm’s technological competence is likely to be strong if it has more internal technological resources and has generated more innovations in the past (Danneels, 2002, 2007; Srivastava, Gnyawali, & Hatfield, 2015). The competence aspect of AC underlines the path dependent nature of AC: if firms do not have existing competence or lack relevant knowledge and learning skills in the beginning, they would struggle in identifying and understanding new external trends (Cohen & Levinthal, 1990). Delay in recognizing the trends and the time needed to catch up could make firms locked out (Schilling, 1998).

Measures used in the empirical literature to capture the competence aspect of AC include the number of patents filed (Nooteboom et al., 2007), stock of prior patents (Dushnitsky & Lenox, 2005a), and share of patents of a firm within the industry (Srivastava et al., 2015). Others have used patent citations (Kim & Inkpen, 2005) and number of unique patents (Srivastava et al., 2015). Yet others have used non-patent measures of knowledge stock such as the number of scientific publications (Kang, 2012), number of technological certifications received (Su, Dhanorkar, & Linderman, 2015), and number of prior product innovations (Estrada et al., 2010).

Process is the third aspect of AC used in the literature (Jansen, Van Den Bosch, & Volberda, 2005; Lane et al., 2006), and is relatively new. The process aspect is rooted in the researchers’ views of AC “as a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge” (Zahra & George, 2002: 186) and as being embedded in the organizational practices developed and used in order to facilitate external learning (Todorova & Durisin, 2007). Volberda and colleagues (2010) underscored the need for more explicit attention to the process aspect of AC. Expressed rules, heuristics, norms and
practices are noted as observable measures (Lewin et al., 2011), and practices such as conducting regular market search, having regular meetings to discuss the impact of new market trends, or examining others’ patents and industry magazines for external knowledge represent the process aspect of AC (Jansen et al., 2005).

Jansen and colleagues (2005) is one of the early empirical studies to examine the process aspect of AC, and they did so using the survey method. They explored the role of cross-functional interfaces and socialization tactics inside the organization for AC development. Following Jansen and colleagues (2005) and adapting their survey items, researchers have examined the spectrum of AC processes related to acquisition, assimilation, transformation, and exploitation. Some researchers (e.g. Zhao & Anand, 2009) examined practices related to sharing of information and knowledge, others focused on frequency of acquisition and dissimulation of external knowledge (Liao, Welsch, & Stoica, 2003), and yet others examined structures and routines for knowledge transfer (Matusik & Heeley, 2005).

Before proceeding to the outcomes of AC, we make two important observations. First, while the three aspects of AC are distinct, they are not mutually exclusive. A firm’s current effort helps to develop future competence. In addition, practices and processes could reflect the level of effort and help develop competence (Eggers & Kaplan, 2013). Overlap also indicates convergence of the three aspects on the larger construct. Second, while the three aspects cover the majority of discussion on AC, some measures used in the literature are excluded from our analysis (illustrated as “others” in Table 2-1) because either they do not fit in the three aspects or the volume of empirical research on them is rather small. Examples are unit size (Belkhodja, 2014), sales (Jang, 2012), and intangible assets (Cieslik & Hagemeyer, 2014) of a firm. Overlap of practices (Lane & Lubatkin, 1998) and technological distance (Bierly, Damanpour, & Santoro,
firms are dyad-specific AC. We excluded the dyad-specific AC because of the confusion of AC (a firm’s knowledge) with external knowledge (partner’s knowledge) that is being sought. We argue that while it is important to understand AC at the dyad-level, knowledge or organizational similarities between firms are part of the external knowledge characteristics, but not a firm’s internal ability. These decisions are in line with our focus on streamlining the literature, and we will visit the issue of AC mechanisms and external knowledge characteristics later.

**Outcomes of AC: Knowledge Generation, Innovation Generation, and Firm Performance**

We systematically reviewed the various outcomes of AC examined in the literature and grouped them into three main categories: knowledge generation, innovation generation, and firm performance. Table 2-2 provides a summary of our categorization of the literature into the key outcomes.

[Insert Table 2-2 about here]

*Knowledge Generation* refers to the knowledge output, including scientific, technological, organizational, or general knowledge (Lane et al., 2006) developed by the firm. While firms could generate knowledge by utilizing both internal and external knowledge, the focus here is on knowledge acquired from outside the firm. Thus, knowledge generation, as intended here, is different from learning by doing internally through practice (Foster & Rosenzweig, 1995; Ying, 1967). Empirical measures of knowledge generation include the rate of external learning (Schildt, Keil, & Maula, 2012), knowledge transfer (Reiche, 2011), and improvement in the firm’s stock of knowledge. Studies have often used survey items asking responses about the amount of knowledge received (Chang, Gong, & Peng, 2012a), the rate of
knowledge transfer (Reiche, 2011), and improvements in the stock of knowledge (Zhao & Anand, 2009).

The second outcome of AC is *Innovation Generation*, which refers to the development of new intellectual properties, new products or processes, and new services by utilizing external knowledge (Lane et al., 2006). While the knowledge output of AC is knowledge generation, the commercial output of AC is innovation generation (Lane et al., 2006). Empirical measures used to capture innovation generation include patent-based measures such as total number of patents generated (Rothaermel & Alexandre, 2009), exploitative patents generated, i.e., patents in technological classes where the firm is currently active (Nootboom et al., 2007), and explorative patents generated, i.e., patents in technological classes where the firm is currently inactive (Gisling et al., 2008). New product measures include the number of new products and services (Nambisan, 2013), adoption of new knowledge in software development (Carlo, Lyytinen, & Rose, 2012), and rate of innovation (Tsai, 2001). Some studies have used survey items asking respondents to rate the company’s new product development program (Ferreras-Mendez, Newell, Fernandez-Mesa, & Alegre, 2015) and new products’ features (Lawson, Tyler, & Potter, 2014) compared to those of competitors.

It is important to note that the concepts of exploitation and assimilation (Zahra & George, 2002), which are commonly used as elements of AC (Chang, Gong, Way, & Jia, 2012b; Fernhaber & Patel, 2012; Zacharia, Nix, & Lusch, 2011), appear similar to knowledge generation (Cereola, Wier, & Norman, 2012; Elbashir, Collier, & Sutton, 2011; Saraf, Liang, Xue, & Hu, 2013) and innovation generation (Bierly et al., 2009; Nambisan, 2013; Nooteboom et al, 2007), which are examined as outcomes of AC. Volberda et al. (2010) also presented exploitation as both an element of AC and an outcome of AC. In addition, some papers use patents to measure
the outcome of AC (e.g. Nooteboom et al., 2007; Phene et al., 2006; Rothaermel & Alexandre, 2009), whereas others use patents to measure AC (e.g. Dushnitsky & Lenox, 2005a, b; Giarratana & Mariani, 2014; Penner-Hahn & Shaver, 2005). In the spirit of reduction of conceptual ambiguity, we underscore the importance of a temporal consideration in future research: existing knowledge and expertise (such as current stock of patents) reflect AC whereas new knowledge and expertise generated by leveraging external knowledge is the outcome of AC.

The third outcome of AC is Firm Performance. Measures of firm performance studied in the AC literature include financial profitability, such as ROA (Bergh & Lim, 2008), ROE (Chin-Jung & Ming-Je, 2007), and ROI (Chang et al., 2012a). Researchers have also examined sales growth (Patel, Kohtamäki, Parida & Wincent, 2015; Zahra & Hayton, 2008) and stock market reactions, such as IPO valuation (Xiong & Bharadwaj, 2011) and cumulative abnormal returns (Sears & Hoetker, 2014). Firm performance is more distant than the other two AC outcomes and is clearly different from the aspects of AC.

We note the temporal nature of the three outcomes. For example, knowledge generation would be the most proximal or immediate outcome, followed by innovation generation, and then firm performance. Both knowledge generation and innovation generation could influence a firm’s performance (e.g. Chang et al., 2012a; Tsai, 2001).

2.3 META-ANALYSIS OF KEY ASPECTS AND KEY OUTCOMES OF AC

We used the conceptual synthesis of the literature as discussed above as a basis to conduct meta-analysis. Meta-analysis helps to synthesize empirical findings, identify patterns, and provide fine-grained insights into the relationship between different aspects and outcomes of AC. Meta-analysis also allows us to compute an estimate of the mean effect size (Hunter & Schmidt, 2004) and provides information on the significance of the discovered mean effect size
by computing its confidence interval. We closely followed established guidelines (Crook, Ketchen, Combs, & Todd, 2008; Drees & Heugens, 2013; Heugens & Lander, 2009) and considered different approaches used in previous meta-analysis studies in making our method choices.

**Literature Search Process and Criteria for Inclusion of Studies**

To identify relevant articles, we employed four complementary literature retrieval procedures and four selection criteria (see Table 2-3 for a summary of the search process and selection filters). For the literature search process, we first examined the EBSCO Business Source Complete database and searched for papers from 1990 (the year when Cohen and Levinthal’s seminal paper was published) to June 2016 with the term “absorptive capacity” in the title, abstract, or author specified keywords. This step yielded 1141 published studies. Second, to maintain journal quality, we included studies published in journals included in the Institute for Science Information (ISI) Web of Knowledge Journal Citation Reports (JCR). The ISI web of knowledge JCR includes a comprehensive converge of the most influential journals around the world. Our final journal list is consistent with the previous published meta-analyses in macro areas (Drees & Heugens, 2013; King, Dalton, Daily, & Covin, 2004; Rosenbusch, Rauch, & Bausch, 2013). Third, we manually searched the ISI journals for recent publications. Lastly, to mitigate the potential file-drawer problem (Rosenthal, 1979), we obtained unpublished studies and working papers by searching doctoral dissertations and the Academy of Management conference proceedings. We contacted the authors directly if the paper was not available online. We gathered full texts of 88 dissertations and 47 conference papers. These literature search efforts yielded a dataset of 841 studies.

[Insert Table 2-3 about here]
We employed four criteria to determine a study’s inclusion for meta-analysis. First, we excluded all non-empirical papers and empirical papers that used AC as a theoretical lens but did not empirically measure or test AC. Second, we excluded papers that did not report sample sizes, pairwise correlations or regression coefficients between AC and the dependent variable, and the standard errors of the coefficients. Third, since we limited our review to papers that examined firm-level AC and firm-level outcomes, we excluded papers that examined AC as the dependent variable and papers that did not examine AC and its outcomes at the firm level. Lastly, we excluded studies that used the same sample that was already counted. For example, dissertations and conference papers are often published later in academic journals using the same dataset. To avoid over-representation of studies, we included only one study if multiple papers used the same sample (Arthur, Bennett, & Huffcutt, 2001). The above selection filter yielded 203 empirical studies (174 published studies, 27 dissertations, and 2 conference papers) with 492 reported bivariate correlations, and 2,580,751 sampled observations (i.e. combined sample size from each individual study).

Data Coding Procedures

We coded information from the 203 empirical studies using procedures recommended by Lipsey and Wilson (2001). We first developed a coding protocol to extract information from each individual study. We collected the bivariate correlation $r$ between AC and the dependent variable, study sample size, regression coefficients between AC and the dependent variable, the standard errors of the regression coefficients, and statistical artifacts such as measurement reliability. We also collected information on the empirical measurements of AC and the outcomes examined. Two authors coded a subsample of randomly selected papers independently. We had 100% agreement on most of the straightforward information extracted from each paper.
(e.g. sample size, pairwise correlation, regression coefficient) but some disagreements existed on judgment-based coding (e.g. the categorization of AC measures and the dependent variable), leading to inter-rater agreement of 96.92%. We resolved the disagreements through discussion in the entire authorship team and further refined the coding protocol. One coauthor coded the rest of the sample after 100% consistency was ensured.

We have already described the aspects and outcomes of AC, so we do not discuss those here. Please note that classification of the measures of the aspects and outcomes are summarized in Tables 2-1 and 2-2, respectively.

Meta-Analytical Decisions and Procedures

Choice of the Effect Size Metric. The focal relationship between AC and the dependent variable in a given sample could be captured using both the Pearson product-moment correlation ($r$) and the partial correlation coefficient ($r_{xy.z}$). Even though $r$ is more commonly used in published meta-analysis studies in management (Geyskens, Krishnan, & Steenkamp, 2009), scholars have recently argued that use of $r_{xy.z}$ has several important benefits over $r$. For example, $r_{xy.z}$ indicates the relationship between AC ($x$) and the DV ($y$) given a set of control variables ($z$), but the influence of control variables could not be reflected in $r$. In addition, $r$ does not imply causation. However, $r_{xy.z}$ provides at least an indicative basis for assessing causal relationships (Karna, Richter, & Riesenkampff, 2015; van Essen, Otten, & Carberry, 2015). To overcome the limitation of a single approach, we followed previous studies (Carney, Gedajlovic, Heugens, Van Essen, & Van Oosterhout, 2011) and used both effect size metrics – we used $r$ for our primary analysis and $r_{xy.z}$ as robustness checks. We computed $r_{xy.z}$ based on the formula $r_{xy.z} = \sqrt{t^2/(t^2 + df)}$ (Greene, 2003) using information provided in regression tables ($t$ refers to the $t$-statistic and $df$ refers to the degree of freedom). Since this formula always produces a positive
number, we converted the \( r_{xy,z} \) to a negative number if the regression coefficient was negative (Carney et al., 2011; Greene, 2003).

For both effect sizes, we followed previous studies and corrected for skewness in the effect size distribution by applying the Fisher’s Z transformation (Drees & Heugens, 2013; Geyskens, Steenkamp, & Kumar, 2006; Lipsey & Wilson, 2001). Z-transformed correlations have the advantage of being approximately normally distributed. In addition, Z transformation allows the sample variance to be only dependent on sample size but not on the population correlation. Therefore, z-transformation allows optimal weighting of the effect sizes (Geyskens et al., 2009). Please refer to Table 2-4 for a summary of the meta-analytic procedures.

Correction for Study Artifacts. We corrected the observed correlation for biases arising from the following artifacts: 1) measurement error, 2) range restriction, 3) dichotomization of continuous variables, and 4) sampling error (Hunter & Schmidt, 2004). Measurement error could cause study results to be systematically lower than they would have been had the measures not included the random error of the measurement. To correct for measurement error, we followed previous studies (Crook et al., 2008; Dalton, Daily, Certo, & Roengpitya, 2003; Lee, Kirkpatrick-Husk, & Madhavan, 2014) and used a conservative 0.8 reliability estimate for studies that did not report reliability statistics. We made correction for attenuation due to error of measurement using the formula \( r_c = \frac{r_{xy}}{\sqrt{r_{xx}r_{yy}}} \) (Hunter & Schmidt, 2004: 45). Following Rosenthal (1991), range restrictions were set at 1.0, and none of the studies in our sample included a dichotomization of a truly continuous variable. Finally, to correct for sampling error, we followed Lipsey & Wilson’s (2001) procedure for analysis and assumed a random effects model. Since the heterogeneity of our effect size distribution is substantial, it violates the key
assumptions of fixed effect models that all the studies included in the analysis are functionally identical and based on identified population (Hedges & Olkin, 1985). Random effects models are preferred over fixed effects approaches as the former yield more conservative estimates of the focal effect with more realistic Type II error rates (Geyskens et al., 2006; Lipsey & Wilson, 2001).

Nonindependence. Nonindependence arises when multiple effect sizes are reported from the same sample. For example, if a study uses multiple measures to operationalize AC, then multiple effect sizes can be derived from this single study, and the nonindependence among the effect sizes may influence the precision of the mean effect size estimate (Arthur, Bennett, & Huffcutt, 2001). If effect sizes derived from the same sample are treated as if they are independent data points, then the same sample would be overrepresented. However, if we only include one effect size from each sample, we would lose the valuable information that is provided by additional effect sizes. Therefore, we followed previous published meta-analyses (Carney et al., 2011; Geyskens et al., 2006; Heugens & Lander, 2009) and used a combined strategy. If the multiple effect sizes are based on different measures of AC (for example, a single study used two alternative measures of AC such as R&D intensity and patent stock) or outcomes (for example, a study included both innovation and firm performance as dependent variables), we then included each individual effect size in the sample. If the multiple effect sizes are based on different dimensions of the same measure (for example, one study measured AC using the patent stock during the last 3 years, 5 years, and 10 years, and reported 3 different effect sizes), we then pooled the multiple effect sizes into a single composite. Following recommendations from Geyskens et al. (2009), if correlations among the dependent effect sizes are available, we followed procedures described in Hunter & Schmidt (2004: 435-439) to compute the composite
effect size. If correlations among the dependent effect sizes were not available, we then computed the average.

Identification of Outliers. There are several papers in our sample that used extremely large samples (e.g. papers using panel data reported a large number of firm-year observations) or reported extreme values of correlations (e.g. paper using past patent stock to predict the generation of new patents). Therefore, it is important for us to identify outliers and compare results using the full data set and results using the dataset excluding outliers. Following recommendations from Geyskens et al. (2009), we used the sample-adjusted meta-analytic deviancy statistic (SAMD) method (Beal, Corey, & Dunlap, 2002; Huffcutt & Arthur, 1995) to identify outliers. An effect size is identified as an outlier if its absolute value of SAMD-Z is above 20, which is a good threshold based on the visual presentation of outliers. We identified 8 potential outliers and conducted a robustness check without the outliers.

Results

Results of meta-analysis using the full sample of Pearson product-moment correlations are shown in Table 2-5. As described earlier, we focus on the three aspects of AC and three outcomes. The measures excluded from the three aspects and the three outcomes are included in the row marked “others”.

Our analysis reveals several interesting findings. First, the average corrected effect size ($r_c$) of .31 with low standard error (.02), small confidence interval (.28 to .34), and significant $p$ value (.00) show that AC has a strong positive effect on firm outcomes. The average corrected effect size of .31 means that 31 percent of the utility available from predicting firm differences in knowledge generation, innovation generation, and firm performance is provided by AC. This suggests that AC is indeed a powerful construct.
Second, when the effects of the three aspects of AC are examined separately, the process aspect has the strongest positive effect ($r_e=0.44$, $p<0.01$). The effort aspect shows a weaker but positive and significant effect ($r_e=0.23$, $p<0.01$). The results are rather ambiguous (as illustrated by the confidence interval ranging from negative to positive, high standard errors, and insignificant $p$ values) regarding the competence aspect of AC. Third, results on the effects of AC on the three outcomes (knowledge generation, innovation generation, and financial performance) show that the effects are stronger on innovation generation ($r_e=0.37$, $p<0.01$) and weaker on knowledge generation ($r_e=0.30$, $p<0.01$) and firm performance ($r_e=0.29$, $p<0.01$). The strongest positive effect on innovation generation confirms the original conceptualization that AC contributes to firm innovation (Cohen & Levinthal, 1990).

Lastly, when we pair different aspects of AC with different outcomes, the results show some fine-grained patterns. The effort aspect pairs the best with the knowledge generation outcome ($r_e=0.34$, $p<0.01$) and the competence aspect pairs the best with the innovation generation outcome ($r_e=0.95$, $p<0.01$). The effect sizes of the process aspect are consistently strong across all outcomes ($r_e=0.42$ to 0.47, $p<0.01$). These findings suggest that investing in R&D is most important for the generation of new knowledge, whereas having more existing knowledge and expertise could largely influence a firm’s generation of future innovations, and having routines and process could potentially facilitate all outcomes. Figure 2-1 illustrates the key relationships between different AC aspects and outcomes.

We performed two additional analyses to cross-check our results and ensure that the results are robust. First, as described earlier, we removed the 8 potential outliers from our sample
and reran the analysis. Table 2-6 presents the results after removing the outliers. The results do not differ greatly from our earlier analysis except for one change: the effect size of the competence-innovation pair becomes weaker (from $r_\varepsilon=0.95$ to $r_\varepsilon=0.76$) and insignificant (from $p<0.01$ to $p>0.10$). This change occurred since most of the outliers are from studies that used patent-based measures, had large samples, and reported extremely large correlation numbers. The change in the magnitude of the effect size suggests potential autocorrelation (Box, Jenkins, & Reinsel, 1994), which may occur when studies use past patent stock to predict generation of new patents. The change in significance also means that the competence-innovation relationship is rather unclear.

[Insert Table 2-6 and 2-7 about here]

Second, we performed our analysis using the partial correlation coefficients. The key difference between the partial correlation coefficient and the Pearson correlation is that partial correlation coefficient examines the relationship between AC and firm outcomes while taking other control variables into account. As shown in Table 2-7, the overall patterns of relationships do not differ greatly from previous results. However, mean effect sizes calculated using partial correlation coefficients are much lower than those calculated using Pearson product moment correlations. For example, for the overall relationship, $r_\varepsilon$ changed from 0.31 to 0.11. Nonetheless, most of the effect sizes are still statistically significant. The change in the magnitude of effect sizes underscores the importance of considering other factors when examining the effect of AC.

Overall, the findings across different analyses consistently show that AC does matter for firm outcomes. Among the three aspects of AC, the process aspect has the strongest effect. Among the three outcomes, AC has the strongest influence on innovation. The effort aspect of
AC has the strongest effect on knowledge generation, and the process aspect has strong effects on all outcomes, but the effect of the competence aspect is rather ambiguous.

### 2.4 MECHANISMS UNDERLYING THE AC-OUTCOMES RELATIONSHIP

With the synthesis of results on the effect of AC on outcomes based on the meta-analysis, we now proceed to provide an explanation of the causal mechanisms through which AC impacts outcomes. We note that more than half of AC papers (57%) talked rather generally about AC as “ability to learn” but did not discuss any specific mechanism of AC in developing their hypotheses. Whene
erver possible, we draw from the literature in discussing the mechanisms. Since the effectiveness of the various mechanisms is likely to depend on the characteristics of external knowledge being sought, we also provide a brief discussion of such characteristics and relate them to the mechanisms.

**Key AC Mechanisms**

While the theoretical AC papers discuss AC mechanisms, many of them have reconceptualized AC and added or revised AC mechanisms (Lane et al., 2006; Todorova & Durisin, 2007; Zahra & George, 2002). There is an apparent lack of clarity and agreement on what those mechanisms are, and empirical papers often use idiosyncratic arguments based on the purpose of their studies. Despite the inconsistencies, we find that there is a general consensus in the literature that AC mechanisms involve two essential elements: acquiring external knowledge and deploying external knowledge (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Todorova & Durisin, 2007; Zahra & George, 2002). Our review of the literature suggests that effective acquisition of external knowledge involves two underlying mechanisms: *searching* and *valuing*. The search mechanism is about identifying and gaining access to new external knowledge, while the valuing mechanism is about screening and assessing usefulness of the knowledge for the firm.
Further, effective deployment of external knowledge involves two underlying mechanisms: *assimilating* external knowledge and *transforming* external knowledge. Assimilation is about understanding and accepting the external knowledge, whereas transformation is about processing and recombining external knowledge. We excluded “commercialization” or “exploitation” of external knowledge as AC mechanisms as they often overlap with AC outcomes (e.g. Gilsing et al., 2008; Nooteboom et al., 2007) as noted earlier. Below we discuss these mechanisms.

**Searching External Knowledge.** First and foremost, acquiring external knowledge involves reaching out and identifying potentially valuable external knowledge (Lane et al., 2006). The search mechanisms have been implied in the literature through terms such as “acquisition” (Zahra & George, 2002) and “exploratory learning” (Lane et al., 2006). External knowledge needs to be first “identified” (Fernhaber & Patel, 2012) and “accessed” (Engelen, Kube, Schmidt, & Flatten, 2014) by a firm in order to benefit from it. Knowledge search could vary in terms of its intensity, speed, and direction (Zahra & George, 2002). Effective search mechanisms can help a firm in identifying distant, diverse, and unique knowledge from the external environment (Patel et al., 2015; Tsai, 2001) and can improve the efficiency and timing of a firm’s discoveries (Fabrizio, 2009).

**Valuing External Knowledge.** Valuing involves evaluating the relative importance of the external knowledge to the firm’s own operations. This mechanism has been illustrated in the literature through the terms “recognizing the value” (Cohen & Levinthal, 1990; Todorova & Durisin, 2007), “knowing what to learn” (Lane & Lubatkin, 1998) and having “selection regimes” (Lewin et al., 2011). Shared cognition and other organizational filters can influence which external knowledge is considered relevant, useful, and important (Todorova & Durisin,
2007). Literature also suggests that firms differ in how they “interpret” (Penner-Hahn & Shaver, 2005), “evaluate” (Engelen et al., 2014), and eventually “screen” external knowledge (Rothaermel & Alexandre, 2009).

**Assimilating External Knowledge.** Assimilation involves processing and absorption of external knowledge, AC literature has been quite consistent in identifying assimilation as a key mechanism (Lane et al., 2006; Lane & Lubatkin, 1998; Lewin et al., 2011; Zahra & George, 2002). Research suggests that firms need to “understand” (Fabrizio, 2009), “absorb” (Godart, Shipilov & Claes, 2014), and “integrate” (Tsai, 2009; Tsai, 2001) valuable external knowledge. Scholars have also argued that organizational and managerial biases such as competency traps (Srivastava & Gnyawali, 2011) can inhibit a firm’s receptivity to external knowledge and therefore limit its assimilation.

**Transforming External Knowledge.** Transforming external knowledge refers to “refining” (Zahra & George, 2002), “adapting” (Todorova & Durisin, 2007), “renewing” existing interpretation (Patel et al., 2015), and “converting” (Tsai, 2009) external knowledge for new usage. Some scholars (Todorova & Durisin, 2007) suggest that transformation could be an alternative mechanism to assimilation. They argue that when the new external knowledge fits the existing cognitive schemas well, the new information is only slightly altered to improve the fit, thus knowledge is assimilated; when the new external knowledge cannot be altered to fit the existing knowledge structure, then the existing cognitive structures must be transformed to adapt to the new information that firms could not assimilate (Todorova & Durisin, 2007). In this sense, transformation of existing knowledge structure is necessary when the external knowledge cannot be assimilated.
We now proceed to briefly explain how the characteristic of external knowledge could influence the effectiveness of the AC mechanisms we have described.

External Knowledge Characteristics

Prior literature has identified several variables external to the firm (Lewin et al., 2011; Nooteboom et al., 2007; Patel, Terjesen, & Li, 2012; Vasudeva & Anand, 2011) and also internal to the firm (Engelen et al., 2014; Liao et al., 2003; Wales, Parida, & Patel., 2013) as contingent conditions influencing the effects of AC on firm outcomes. We focus on external contingent conditions because the theory of absorptive capacity is fundamentally about a firm’s effectiveness in leveraging and benefitting from external knowledge. We focus on external knowledge characteristics and categorize it along four key aspects: knowledge potential, knowledge familiarity, knowledge diversity, and knowledge type.

*External Knowledge Potential.* In examining the interaction of a firm’s AC with external knowledge sources, prior studies have used a wide variety of variables to essentially probe the role of availability of (or access to) a larger pool of knowledge, which we label as external knowledge potential. For example, a firm’s centrality in a large network (Gilsing et al., 2008), investment in entrepreneurial ventures (Dushnitsky & Lenox, 2005a), external technology sourcing (Rothaermel & Alexandre, 2009), inward centrality of a firm based on inward mobility of employees from other firms (Godart et al., 2014), and centrality of a business unit (Tsai, 2001) indicate the presence of potential opportunities for accessing a larger pool of external knowledge-based resources.

*External Knowledge Familiarity.* Familiarity refers to the extent to which knowledge is similar to the firm’s existing internal knowledge. Knowledge that is more relevant and familiar is easier to assimilate and transfer. Examples of measures that capture knowledge familiarity used
in the literature include technological distance or similarity with alliance partners (Nooteboom et al., 2007; Schildt et al., 2012; Vasudeva & Anand, 2011), and technological relatedness with university research centers (Bierly et al., 2009). In the context of mergers and acquisitions, relatedness of acquisitions (Zahra & Hayton, 2008), technological distance (Makri, Hitt, & Lane, 2010; Sears & Hoetker, 2014) and technological complementarity (Makri et al., 2010) with target firms also indicate external knowledge familiarity. We note that some literature has suggested knowledge familiarity as “relative absorptive capacity” (Lane & Lubatkin, 1998) with the logic that greater familiarity with the knowledge of the partners makes it easier to understand the knowledge. We argue that it is more appropriate to consider knowledge familiarity as a characteristic of external knowledge but not as absorptive capacity. When firms engage in exploratory search, they often encounter valuable knowledge that is less familiar to them. Firms that have the necessary absorptive capacity would be able to leverage such knowledge (Nambisan, 2013; Nooteboom et al., 2007). In other words, high absorptive capacity would facilitate assimilation of unfamiliar or distant knowledge.

**External Knowledge Diversity.** A firm trying to leverage external knowledge is exposed to a wide variety of knowledge. Knowledge diversity can arise from reaching out to different sources of knowledge or even reaching out to sources that possess a variety of knowledge. Since innovation is essentially a recombinant activity (Fleming & Sorenson, 2001), access to wide variety of ideas and knowledge could be very helpful in innovation activities. When external knowledge is diverse, learning becomes rather challenging. High absorptive capacity, though, could help to facilitate understanding and assimilation of very diverse knowledge. Examples of measures that capture external knowledge diversity include diversity of a firm’s alliance portfolio (Vasudeva & Anand, 2011), breadth of knowledge sourcing (Ghisetti, Marzucchi, &
Montresor, 2015; Nicholls-Nixon & Woo, 2003), network position in terms of structural hole (Shipilov, 2009), and internationalization of R&D activities providing access to unique pockets of knowledge (Penner-Hahn & Shaver, 2005).

**External Knowledge Type.** The nature of knowledge a firm can get from external sources is also very important in determining the effectiveness of its absorptive capacity. Knowledge can vary in terms of the degree of tacitness and complexity, and the extent to which it is specialized (Bierly et al., 2009; Winkelbach & Walter, 2015). Different types of partners such as universities, customers, suppliers, competitors, and relationships such as R&D alliances, R&D consortiums offer knowledge that varies in terms of its complexity, tacitness, and specialization (Bierly et al., 2009; Fabrizio, 2009; Tsai, 2009; Xiong & Bharadwaj, 2011). Benefitting from such complex, tacit and specialized knowledge would require presence of high absorptive capacity.

**External Knowledge Characteristics and Importance of Different AC Mechanisms**

Even though scholars have started to examine how AC influences outcomes under different external knowledge conditions (Bierly et al., 2009; Ghisetti et al, 2015), we still know very little about how the specific AC mechanisms work in relation with different external knowledge, and how different AC aspects are connected to different AC mechanisms. As a start to develop this fine-grained understanding, we next illustrate the relationships among AC aspects, mechanisms, and external knowledge characteristics.

We suggest that the *effort* aspect of AC more directly captures the *searching* and *valuing* mechanisms. Firms making greater innovation effort are more willing to search for new knowledge and they are also more receptive to external knowledge (Srivastava et al., 2015). Effort indicates a firm’s level of motivation for searching new knowledge, and firms with greater
effort exhibit more openness to external knowledge (Caloghirou, Kastelli, & Tsakanikas, 2004). We suggest that the competence aspect of AC more directly captures the assimilating and transforming mechanisms. A firm’s existing capability and past success demonstrate its developed abilities in absorbing new knowledge and utilizing that knowledge. Since the process aspect of AC could potentially capture many different organizational practices for external learning, it is conceivable that process may relate to multiple mechanisms.

When it comes to external knowledge potential, the effort aspect of AC becomes more salient. Greater efforts to search and mobilize external knowledge is more effective when a firm is well positioned to access external knowledge (such as external knowledge in a network or geographic cluster). When the firm recognizes the value of that external knowledge, the firm is able to acquire the knowledge more effectively. For instance, firms that make greater efforts in identifying valuable knowledge while making CVC investments also put mechanisms in place to mobilize that knowledge post making the investment. The due diligence they do in identifying the valuable knowledge and the mechanisms they put in place to mobilize it help them leverage that knowledge more effectively (Dushnitsky & Lenox, 2005a).

When the external knowledge diversity is high or external knowledge type is highly specialized, tacit or complex, the role of assimilation and transformation mechanisms becomes more critical. When the external knowledge is more diverse or more complex, firms face greater hurdles in integrating and understanding that knowledge. A firm with greater knowledge processing capacity can benefit more effectively from such external knowledge. Therefore, the competence aspect of AC becomes particularly critical when the external knowledge is more tacit, complex, specialized or highly diverse. For example, partnership with universities could be valuable, but only if partnering firms are also engaged in more basic research (Fabrizio, 2009).
When the external knowledge is complex, prior knowledge base and experience in that area are more helpful in developing a better understanding of the knowledge (Winkelbach & Walter, 2015).

When the *external knowledge familiarity* is low, or the external knowledge is more distant, benefiting from such knowledge could be challenging. One may expect that the presence of greater competence would help firms in assimilating and transforming distant knowledge, but the prior literature has found firms often fail to do so (Nooteboom et al., 2007). Firms with greater technological competence can also suffer from the ‘not-invented-here’ (NIH) syndrome (Cohen & Levinthal, 1990; Srivastava & Gnyawali, 2011). Due to the NIH syndrome, firms tend to focus more on their internal knowledge and do not value external knowledge as much, therefore such firms also may make less effort to mobilize the external knowledge. Therefore, when it comes to leveraging external knowledge that is more distant, the effort aspect of becomes critical.

2.5 DISCUSSION AND IMPLICATIONS

Rapid growth of research on AC underscores the increasing importance of the concept. The growth, however, has also resulted in the loss of focus on the core aspects of AC, fragmentation of theoretical explanations, and proliferation of AC measures. Given the use of AC to “loosely encompass and account for a set of diverse phenomena” (Hirsch & Levin, 1999: 200) and fractioned views on the topic (Volberda et al., 2010; Zahra & George, 2002), scholars have stressed the need for greater conceptual clarity (Lane et al., 2006), but those issues have continued. Further, despite having a large body of empirical literature, there is little effort to synthesize the findings. Consequently, we know little about the extent to which AC matters for different firm-level outcomes. The lack of synthesis, particularly of the empirical literature,
could be potentially problematic for developing cumulative knowledge, and for scientific and appropriate use of the research findings (Rousseau, Manning, & Denyer, 2008).

This paper was accordingly motivated by the need to distill the core aspects of the AC literature, to discern and illuminate key theoretical insights, to assess the empirical state of the literature, and to synthesize key findings. Through a systematic review of the literature, we identified three core aspects of AC—effort, competence, and process—and three important outcomes—knowledge generation, innovation generation, and firm performance. We then performed meta-analysis to distill empirical findings and highlighted the key areas where AC matters the most. We also reviewed the literature and illustrated key theoretical mechanisms of AC, key characteristics of external knowledge, and how the AC mechanisms would work when considered together with the characteristics of external knowledge.

Contributions

We contribute to the literature in three important ways. First, our distillation of the literature and illumination of the core aspects of AC provide a much-needed conceptual coherence on AC. We show that many conceptualizations and measures of AC can be grouped into three aspects, each with a distinct focus and role. We illustrate that the effort aspect provides a broad-based potential, the competence aspect provides the current ability, and the process aspect provides the routines and tasks for leveraging external knowledge. Our review thus provides a basis for future scholars to be explicit about the specific aspect of AC and use appropriate measures that match with the aspects of AC. Furthermore, our identification of the three important outcomes studied in AC research, i.e., knowledge generation, innovation generation, and firm performance helps to understand where and how AC matters for firm level outcomes. We found that the effort and process aspects of AC showed consistent impacts on all
three firm outcomes, and the process aspect had stronger effects. The competence aspect had strongest impact on innovation generation, but had little impact on knowledge generation and firm performance. These findings provide important insights regarding which aspects of AC have most significant impact on which firm outcomes. We believe the clarity provided in this paper will help researchers to design and conduct future research in a more focused manner so that the findings become comparable and helpful to develop a more coherent body of knowledge.

Second, our articulation of theoretical mechanisms that are specific to AC—focused on benefiting from external knowledge—would help to increase conceptual clarity and rigor in future research. When drawing upon the theory of AC, it is important to specify the underlying AC mechanisms and discuss how the measurement of AC corresponds to those mechanisms. Without being explicit on the AC mechanisms, theoretical discussion becomes vague, and the danger of AC being used as a general-purpose construct intensifies. As Cohen and Levinthal (1990) explained, the effects of R&D (which is one important aspect of AC) could occur independent of AC. For example, firms could use R&D investments and R&D employees to develop internal projects (Kelm, Narayanan, & Prinches, 1995) that may help them to develop new products internally (Griliches, 1980). Similarly, the resource-based view (Grant, 1996; Spender, 1996) and recombinant view of innovation (Kogut & Zander, 1992; Fleming, 2001) show that firms with strong internal technological capabilities are more innovative. This direct effect of capability could occur without AC. So, it is important that AC should not be viewed as a catch-all construct. The mechanisms through which AC influences firm outcomes need to be specified. Furthermore, our articulation of external knowledge contingencies that influence the relationship between AC and outcomes underscores the focus of AC on internal ability to leverage external knowledge. It also highlights the varying importance of different AC
mechanisms depending upon the characteristics of external knowledge. We thus provide a foundation for future studies to precisely articulate the mechanisms through which AC impacts outcomes. Accordingly, we believe that our paper has provided the basis for increased conceptual clarity and rigor for future research.

Meta-analysis is helpful in providing assessments of important yet fragmented concepts and relationships (Combs, Ketchen, Crook, & Roth, 2011) and discern areas of empirical consistency. Our third contribution thus lies in the distillation of the empirical findings and discerning of key patterns. We demonstrate that AC has a strong positive effect on firm outcomes. When the specific outcomes are examined, we show that AC has the most consistent and strongest effect on firm innovation. In terms of the aspects of AC, we show that the process aspect has the strongest and most consistent effect on the firm outcomes. Our integration of findings across studies and comparison across the aspects of AC and outcomes of AC thus provide cumulative evidence on this topic and bolster researchers’ and managers’ confidence on the role of AC.

**Future Research Directions**

Equipped with the insights and contributions of this paper, future researchers could design and conduct research in a more rigorous manner. We highlight a few promising directions. First, our study offers a basis for researchers to focus on a particular aspect of AC (i.e. effort, competence, or process) and go deeper into the conceptualization and associated measures. Future scholars can compare and contrast different AC aspects, and identify conditions that alter the relationship between each AC aspect and AC outcome. Second, researchers need to be clear on which aspect of AC they are focusing on and articulate the mechanisms through which that aspect of AC matters for firm outcomes. Very few studies have explored the specifics
of search, value, assimilate, and transform (Engelen et al., 2014; Fabrizio, 2009; Patel et al., 2015). We urge future researchers to develop specific measures that capture these mechanisms and examine whether the specific mechanisms do indeed work the way we have theorized.

Third, our findings from the meta-analysis provide a basis for future researchers to direct their efforts towards streamlining or exploration. Researchers interested in streamlining and development of cumulative knowledge with greater confidence could examine the aspects that were the focus of our meta-analysis, gather more empirical evidence, and provide greater confidence or negate the findings we have reported. Researchers interested in exploring newer aspects could identify important external knowledge contingencies and their interactions with the various aspects of AC. Further, as the literature on external knowledge contingencies grows, it will offer greater opportunities to conduct a meta-analysis of how external knowledge characteristics influence the effects of AC on firm outcomes. Fourth, it is very likely that the different outcomes we have examined are temporal in nature. That is, learning or knowledge generation could be the most immediate outcome of AC, followed by innovation, and then by financial performance. Future researchers could design studies with time-lagged performance outcomes so that we could understand the effects of different aspects of AC on different outcomes over time. Finally, in order to keep the scope of the paper manageable, we did not examine antecedents of AC. Future researchers could investigate how different internal and external conditions shape a firm’s AC.

In conclusion, while the literature on AC has grown substantially, the problems of fragmentation, conceptual ambiguity, and lack of cumulative knowledge have persisted. We believe that our systematic review of the conceptual and empirical literature and meta-analysis of the empirical findings have provided greater conceptual clarity, reduced clutter, and helped
understand key empirical patterns. We also brought back the core of AC as internal ability to leverage external knowledge as originally conceptualized by Cohen & Levinthal (1989, 1990). Our paper thus consolidates the literature to its core and provides a basis for greater rigor in future research.
2.6 REFERENCES


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<table>
<thead>
<tr>
<th>Aspect of AC</th>
<th>Measures Used in the Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effort</td>
<td><strong>Financial Investment in R&amp;D</strong></td>
</tr>
<tr>
<td></td>
<td>o R&amp;D expenditure (Alnuaimi &amp; George, 2016; Dushnitsky &amp; Lenox, 2005a; Ghisetti et al., 2015; Nambisan, 2013; Rothaermel &amp; Alexandre, 2009)</td>
</tr>
<tr>
<td></td>
<td>o R&amp;D intensity as R&amp;D expenditure divided by total sales (de Jong &amp; Freel, 2010; Estrada et al., 2010; Swift, 2016; Tsai, 2001)</td>
</tr>
<tr>
<td></td>
<td>o Firm’s expenditures on R&amp;D activities and training programs divided by its total number of employees (Tsai, 2009)</td>
</tr>
<tr>
<td></td>
<td>o Dummy variable indicating if the firm has an internal R&amp;D department (Pinto, Fernandez-Esquinas, &amp; Uyarra, 2015) or if the firm engages in R&amp;D activities (de Faria et al., 2010)</td>
</tr>
<tr>
<td></td>
<td>o Dummy variable indicating if the firm continuously engages in R&amp;D activities (Xia &amp; Roper, 2008)</td>
</tr>
<tr>
<td></td>
<td><strong>Commitment for Technology Development</strong></td>
</tr>
<tr>
<td></td>
<td>o Number of R&amp;D employees (Huang et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>o Percentage of R&amp;D employees or professional and technological personnel among the total number of employees (Estrada et al., 2010; Luo, 1997)</td>
</tr>
<tr>
<td></td>
<td>o Percentage of firm employees with a master or PhD degree (Xia and Roper, 2008)</td>
</tr>
<tr>
<td></td>
<td>o Survey items asking the percentage of employees with information on up to date technical practices and necessary skills (Matusik &amp; Heeley, 2005)</td>
</tr>
<tr>
<td></td>
<td>o The commitment and concern of the management of the company towards R&amp;D (Expósito-Langa, Molina-Morales, &amp; Tomás-Miquel, 2015)</td>
</tr>
<tr>
<td>Competence</td>
<td><strong>Patent-Based Measures</strong></td>
</tr>
<tr>
<td></td>
<td>o Patent stock: total number of patents (Dushnitsky &amp; Lenox, 2005a; Nooteboom et al., 2007; Wagner, 2011)</td>
</tr>
<tr>
<td></td>
<td>o Filing of patents in the reported period (Pinto et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>o Quality of a firm’s technology portfolio: a count of the citations received by firm’s patents from subsequent patents (Kim &amp; Inkpen, 2005)</td>
</tr>
<tr>
<td></td>
<td>o Innovation speed such as the median year of the patent citations by the firm (Kim &amp; Inkpen, 2005)</td>
</tr>
</tbody>
</table>
Table 2-1  
(continued)  

<table>
<thead>
<tr>
<th>Aspect of AC</th>
<th>Measures Used in the Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Competence (continued)</td>
<td>Non-Patent Based Measures</td>
</tr>
<tr>
<td></td>
<td>o Number of scientific papers published by firm employees (Kang, 2012)</td>
</tr>
<tr>
<td></td>
<td>o Number of prior product innovations (Estrada et al., 2010) or if the company has introduced any innovations in the reported period (Pinto et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>o Number of ISO 9001 certifications in a given year (Su et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>o Health information technology systems inventory (Peng, Dey, &amp; Lahiri, 2014)</td>
</tr>
<tr>
<td>Process</td>
<td>Survey Items Asking Respondents about Organizational Practices</td>
</tr>
<tr>
<td></td>
<td>o Items related to each element of potential and realized AC: acquisition, assimilation, transformation and exploitation (Jansen et al., 2005) or items adapted from Jansen et al. (2005) (Chang et al., 2012b; Larrañeta, Zahra, &amp; González, 2012; Patel et al., 2012; Wales et al., 2013)</td>
</tr>
<tr>
<td></td>
<td>o Items related to the collective and individual dimensions of AC (Zhao &amp; Anand, 2009)</td>
</tr>
<tr>
<td></td>
<td>o Items related to the external knowledge acquisition and intra firm knowledge disseminations dimensions of AC (Liao et al., 2003)</td>
</tr>
<tr>
<td></td>
<td>o Items related to demand pull and science push as two dimensions of AC (Murovec &amp; Prodan, 2009)</td>
</tr>
<tr>
<td>Others</td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Unit size (Belkhodja, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Acquirer size (Li, Li, &amp; Wang, 2016)</td>
</tr>
<tr>
<td></td>
<td>o Technological overlap or distance (Bierly et al., 2009; Dushnitsky &amp; Lenox, 2005a; Sears &amp; Hoetker, 2014; Vasudeva &amp; Anand, 2011)</td>
</tr>
<tr>
<td></td>
<td>o Content analysis of news that reflect a firm’s information technology applications (Joshi, Lei, Datta, &amp; Shu, 2010)</td>
</tr>
<tr>
<td></td>
<td>o Mathematical estimations of the efficiency of absorbing knowhow using econometric models (Xiong &amp; Bharadwaj, 2011)</td>
</tr>
<tr>
<td></td>
<td>o Ratio of intangible assets to total assets (Cieślik &amp; Hagemeyer, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Natural logarithm of sales (Jang, 2012)</td>
</tr>
<tr>
<td></td>
<td>o Dummy variable of if university is a source of collaboration (Harirchi &amp; Chaminade, 2014)</td>
</tr>
</tbody>
</table>
Table 2-2 Summary of the Three Outcomes of AC and the Measures Used

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Measures Used in the Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Knowledge Generation</strong></td>
<td><em>Survey Items Asking Respondents About Knowledge Received or Acquired</em></td>
</tr>
<tr>
<td></td>
<td>o Knowledge received: survey items asking respondents to indicate the amount of knowledge that their subsidiaries received from expatriates (Chang et al., 2012a)</td>
</tr>
<tr>
<td></td>
<td>o Knowledge transfer: survey items asking respondents to rate the extent to which they have made the effort to transfer knowledge (Reiche, 2011) or the degree of which the receipt obtained ownership of the knowledge (Schulze, Brojerdi, &amp; Krogh, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Improvement of the firm’s stock of knowledge: survey items reflecting improvement in the firm’s individual and collective knowledge (Zhao &amp; Anand, 2009)</td>
</tr>
<tr>
<td><strong>Patent Citation</strong></td>
<td><em>Learning rate: the sum of the partners’ unique patents cited by a focal firm</em> (Schildt et al., 2012)</td>
</tr>
<tr>
<td></td>
<td><em>Acquisition or use of regional university knowledge: number of citations in firms’ patents to universities</em> (Acosta, Azagra-Caro, &amp; Coronado, 2016)</td>
</tr>
<tr>
<td><strong>Innovation Generation</strong></td>
<td><em>New Patents</em></td>
</tr>
<tr>
<td></td>
<td>o Total patents: the total number of new patents assigned to the firm in four years (Rothaermel &amp; Alexandre, 2009)</td>
</tr>
<tr>
<td></td>
<td>o Explorative patents: number of patents a firm successfully filed for in year $t$ within patent classes in which it has not been active prior to the given year (Gilsing et al., 2008)</td>
</tr>
<tr>
<td></td>
<td>o Exploitative patents: number of patents a firm successfully filed for in year $t$ within patent classes in which the firm has been active prior to the given year (Nooteboom et al., 2007)</td>
</tr>
<tr>
<td></td>
<td><em>New Products, Services, or Processes</em></td>
</tr>
<tr>
<td></td>
<td>o New products or services: number of new products and services offered (Nambisan, 2013; Carlo et al., 2012)</td>
</tr>
<tr>
<td></td>
<td>o New processes: survey items asking the adoption and use of new knowledge in software development processes (Carlo et al., 2012)</td>
</tr>
</tbody>
</table>
Table 2-2
(continued)

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Measures Used in the Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Innovation Generation (continued)</strong></td>
<td>Other Aspects of Innovation</td>
</tr>
<tr>
<td></td>
<td>o Innovation rate: the number of new products introduced in a unit divided by its target number in a specific year (Tsai, 2001)</td>
</tr>
<tr>
<td></td>
<td>o Innovation speed: survey items asking if the firm could market its products faster (Knockaert &amp; Spithoven, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Innovation performance: survey items in which respondents rate their new product development program in relation to their competitors (Ferreras-Méndez et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>o New product advantage: survey items asking respondents to rate their new product’s unique features and technical performance relative to their competitor’s (Lawson et al., 2014)</td>
</tr>
<tr>
<td><strong>Firm Performance</strong></td>
<td>Profitability</td>
</tr>
<tr>
<td></td>
<td>o ROA (Bergh &amp; Lim, 2008), ROE (Luan &amp; Tang, 2007), ROI (Chang et al., 2012a)</td>
</tr>
<tr>
<td></td>
<td>Growth</td>
</tr>
<tr>
<td></td>
<td>o Sales growth (Patel et al., 2015; Zahra &amp; Hayton, 2008)</td>
</tr>
<tr>
<td></td>
<td>Stock Market</td>
</tr>
<tr>
<td></td>
<td>o Cumulative abnormal return (Sears &amp; Hoetker, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Tobin’q (Setia &amp; Patel, 2013)</td>
</tr>
<tr>
<td></td>
<td>Other Performance</td>
</tr>
<tr>
<td></td>
<td>o Survey items asking the firm’s competitive advantage including the firm’s relative economic and financial performance to its competitors’ (Francalanci &amp; Morabito, 2008)</td>
</tr>
<tr>
<td></td>
<td>o Mixed scale (e.g. a scale that mixes accounting performance, market share and sales relative to its competitors) (García-Morales, Bolivar-Ramos, &amp; Marin-Rojas, 2014)</td>
</tr>
<tr>
<td><strong>Others</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o Level of product diversification (Wang, Ning, &amp; Chen, 2014)</td>
</tr>
<tr>
<td></td>
<td>o Relational capital: survey items asking the existence of profitable relationships and value of them (Vieira, Briones-Penalver, &amp; Cegarra-Navarro, 2015)</td>
</tr>
<tr>
<td></td>
<td>o Healthcare IT adoption: binary variable indicating whether or not a hospital adopts healthcare IT in the observation year (Peng et al., 2014)</td>
</tr>
<tr>
<td></td>
<td>o R&amp;D outsourcing intensity: probability of R&amp;D outsourcing and share of outsourced R&amp;D expenditure (Spithoven &amp; Teirlinck, 2015)</td>
</tr>
<tr>
<td>Description</td>
<td>Starting # of Papers</td>
</tr>
<tr>
<td>-----------------------------------------------------------------------------</td>
<td>----------------------</td>
</tr>
<tr>
<td><strong>Literature Search Process</strong></td>
<td></td>
</tr>
<tr>
<td>1. Searched articles with “absorptive capacity” in their title, abstract, or keyword from 1990 to June 2016</td>
<td>1141</td>
</tr>
<tr>
<td>2. Limited to papers published in the ISI Web of Knowledge JCR list</td>
<td>1141</td>
</tr>
<tr>
<td>3. Searched recent publications that were not shown in the database</td>
<td>706</td>
</tr>
<tr>
<td>4. Searched doctoral dissertations and conference presentations, and contacted authors directly for unpublished work</td>
<td>706</td>
</tr>
<tr>
<td><strong>Criteria for Inclusion of Studies</strong></td>
<td></td>
</tr>
<tr>
<td>1. Removed non-empirical papers and empirical papers that did not measure or test AC</td>
<td>841</td>
</tr>
<tr>
<td>2. Removed papers that did not report sample size, pairwise correlation, or regression coefficient and standard error</td>
<td>259</td>
</tr>
<tr>
<td>3. Removed papers that used AC as DV and papers that did not measure firm-level AC and firm-level outcomes</td>
<td>219</td>
</tr>
<tr>
<td>4. Removed papers with duplicating samples</td>
<td>207</td>
</tr>
</tbody>
</table>
### Table 2-4 Descriptions of Meta Analytic Procedures

<table>
<thead>
<tr>
<th>Procedures</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct for measurement error</td>
<td>We used formula ( r_c = \frac{r_{xy}}{\sqrt{r_{xx}r_{yy}}} ) (Hunter &amp; Schmidt, 2004: 45) to correct for measurement error. For studies that did not report reliability statistics, we followed previous meta-analysis (Connelly, Crook, Combs, Ketchen, &amp; Aguinis, 2015; Dalton et al., 2003) and used a conservative 0.8 reliability estimate.</td>
</tr>
<tr>
<td>Perform Z-transformation</td>
<td>We corrected for skewness in the effect size distribution by applying the Fisher’s Z transformation. Z-transformed correlations have the advantage of being approximately normally distributed and it prepares the data for HOMA procedures.</td>
</tr>
<tr>
<td>Choose random versus fixed effect models</td>
<td>Since the heterogeneity of our effect size distribution is substantial, it violates the key assumptions of fixed effect models that all the studies included in the analysis are functionally identical and based on identified population (Hedges &amp; Olkin, 1985). We, therefore, chose random effects models as they yield more conservative estimates of the focal effect with more realistic Type II error rates (Geyskens et al., 2006; Lipsey &amp; Wilson, 2001).</td>
</tr>
<tr>
<td>Calculate mean effect size</td>
<td>We calculated the mean effect size using HOMA procedures (Hedges &amp; Olkin, 1985) as follows: ( \bar{\tau}<em>c = \frac{\sum (w_l r_c)}{\sum r_c} ), where ( w_l = \frac{1}{s.e. \overline{\phi}^2 + \overline{\phi}^2} ); s.e. is the standard error of the effect size and ( \overline{\phi}^2 ) is the random effect variance component. s.e. ( (z</em>{\tau_i}) = \frac{1}{\sqrt{n_i - 3}} ) and ( \overline{\phi} = \frac{Q_{-(k-1)}}{c} ), where Q is Cochran’s homogeneity test statistic and C is a constant.</td>
</tr>
<tr>
<td>Calculate standard error of mean effect size</td>
<td>We calculated the standard error of the mean effect size as ( s.e. \bar{\tau}_c = \frac{1}{\sqrt{\sum w_i}} ).</td>
</tr>
<tr>
<td>Calculate confidence interval</td>
<td>We calculated the confidence interval of the mean effect size as ( C.I._{.95%} = \bar{\tau}_c \pm 1.96 \times s.e. \bar{\tau}_c ).</td>
</tr>
</tbody>
</table>
## Table 2-5 Results of Meta-Analysis using Pearson Product-Moment Correlation

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>K</th>
<th>N</th>
<th>( r_c )</th>
<th>( SE_{r_c} )</th>
<th>95% CI</th>
<th>Q</th>
<th>( p_Q )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall relationship</td>
<td>203</td>
<td>492</td>
<td>2,580,751</td>
<td>0.31***</td>
<td>0.02</td>
<td>0.28,0.34</td>
<td>278141.64</td>
<td>0.00</td>
</tr>
<tr>
<td>Aspects of AC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effort</td>
<td>76</td>
<td>131</td>
<td>2,184,383</td>
<td>0.23***</td>
<td>0.01</td>
<td>0.20,0.26</td>
<td>44190.38</td>
<td>0.00</td>
</tr>
<tr>
<td>Competence</td>
<td>20</td>
<td>36</td>
<td>62,693</td>
<td>0.35</td>
<td>0.25</td>
<td>-0.14,0.85</td>
<td>101486.44</td>
<td>0.00</td>
</tr>
<tr>
<td>Process</td>
<td>97</td>
<td>215</td>
<td>69,504</td>
<td>0.44***</td>
<td>0.03</td>
<td>0.38,0.51</td>
<td>7559.26</td>
<td>0.00</td>
</tr>
<tr>
<td>Others</td>
<td>46</td>
<td>110</td>
<td>264,171</td>
<td>0.08***</td>
<td>0.02</td>
<td>0.05,0.12</td>
<td>6609.33</td>
<td>0.00</td>
</tr>
<tr>
<td>Outcomes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge Generation</td>
<td>30</td>
<td>74</td>
<td>23,233</td>
<td>0.30***</td>
<td>0.03</td>
<td>0.24,0.36</td>
<td>1530.18</td>
<td>0.00</td>
</tr>
<tr>
<td>Innovation Generation</td>
<td>81</td>
<td>179</td>
<td>2,083,191</td>
<td>0.37***</td>
<td>0.03</td>
<td>0.31,0.43</td>
<td>258848.53</td>
<td>0.00</td>
</tr>
<tr>
<td>Firm performance</td>
<td>74</td>
<td>132</td>
<td>105,534</td>
<td>0.29***</td>
<td>0.03</td>
<td>0.23,0.36</td>
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<td>48</td>
<td>107</td>
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<td>Aspect of AC -&gt; Outcomes</td>
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Note: \( n \) = number of studies; \( K \) = number of effect sizes; \( N \) = total sample size; \( r_c \) = mean effect size for measurement error corrected correlations; \( SE_{r_c} \) = standard error of \( r_c \); \( Q \) = Cochran’s homogeneity test; \( p_Q \) = probability of \( Q \).

*\( p < 0.10 \); **\( p < 0.05 \); ***\( p < 0.01 \)
<table>
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<tr>
<th>Overall relationship</th>
<th>n</th>
<th>K</th>
<th>N</th>
<th>$r_\tau$</th>
<th>$SE_{r_\tau}$</th>
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<th>Q</th>
<th>$p_Q$</th>
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<td>128</td>
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<td>Process</td>
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<td>214</td>
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<td>0.38, 0.51</td>
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<td>0.05, 0.12</td>
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<td>Knowledge Generation</td>
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<td>0.29, 0.33</td>
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<td>Firm performance</td>
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<td>0.02</td>
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</table>
| Note: n= number of studies; $K$ = number of effect sizes; $N$ = total sample size; $r_\tau$= mean effect size for measurement error corrected correlations; $SE_{r_\tau}$= standard error of $r_\tau$; Q = Cochran’s homogeneity test; $p_Q$ = probability of Q.

*p < 0.10; **p < 0.05; ***p < 0.01
Table 2-7 Results of Meta-Analysis using Partial Correlation Coefficients

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<tr>
<th></th>
<th>n</th>
<th>K</th>
<th>N</th>
<th>$r_\tau$</th>
<th>$SE_{r_\tau}$</th>
<th>95% CI</th>
<th>Q</th>
<th>$p_Q$</th>
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<td>0.01</td>
<td>0.08</td>
<td>0.14</td>
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<td>Effort</td>
<td>57</td>
<td>77</td>
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<td>0.01</td>
<td>0.07</td>
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<td>17</td>
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<td>0.05</td>
<td>0.26</td>
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<td>Others</td>
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<td>0.03</td>
<td>0.03</td>
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<td>Knowledge Generation</td>
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<td>0.03</td>
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<td>0.03</td>
<td>0.10</td>
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<td>0.04</td>
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<td>Others</td>
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<td><strong>Aspect of AC -&gt; Outcomes</strong></td>
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<td>0.11</td>
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<td>0.01</td>
<td>0.10</td>
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<td>2</td>
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<td>0.07</td>
<td>-0.13</td>
<td>0.15</td>
<td>5.78</td>
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<tr>
<td>Competence -&gt; Innovation Generation</td>
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<td>5</td>
<td>34,364</td>
<td>0.52**</td>
<td>0.24</td>
<td>0.05</td>
<td>0.99</td>
<td>1713.10</td>
</tr>
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<td>6</td>
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<td>0.07</td>
<td>-0.11</td>
<td>0.18</td>
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<td>Process -&gt; Knowledge Generation</td>
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<td>2</td>
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<td>0.21</td>
<td>-0.31</td>
<td>0.49</td>
<td>22.08</td>
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<tr>
<td>Process -&gt; Innovation Generation</td>
<td>7</td>
<td>7</td>
<td>15,506</td>
<td>0.11**</td>
<td>0.05</td>
<td>0.00</td>
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<td>Process -&gt; Firm Performance</td>
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<td>619</td>
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<td>0.30</td>
<td>-0.35</td>
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Note: n = number of studies; K = number of effect sizes; N = total sample size; $r_\tau$ = mean effect size for measurement error corrected correlations; $SE_{r_\tau}$ = standard error of $r_\tau$; Q = Cochran’s homogeneity test; $p_Q$ = probability of Q.

*p < 0.10; **p < 0.05; ***p < 0.01
**Figure 2-1 Illustration of Key Relationships between Different Aspects of AC and Different Firm Outcomes**

- **Effort**
  - 0.34 to Knowledge Generation
  - 0.24 to Innovation Generation
  - 0.28 to Firm Performance

- **Competence**
  - 0.04 to Knowledge Generation
  - 0.95 to Innovation Generation
  - 0.00 to Firm Performance

- **Process**
  - 0.47 to Knowledge Generation
  - 0.46 to Innovation Generation
  - 0.42 to Firm Performance

**Note:**

- Numbers represent average corrected effect sizes (calculated using the full sample Pearson product-moment correlations)

- Thickness of lines represents the magnitude of effect sizes

- Solid lines represent significant relationships (p<0.05) and dotted lines represent non-significant relationships (p>0.05)
CHAPTER 3 : PAPER TWO

INNOVATION CHOICES IN EMERGING INDUSTRIES: THE DIRECT AND JOINT EFFECTS OF TECHNOLOGICAL CAPABILITY AND CEO EXPERIENCE

3.1 INTRODUCTION

New industry emergence is often triggered by technological discontinuities (Schumpeter, 1934), fuelling new entries and rapid technological development (Anderson & Tushman, 1990). Innovation research suggests that technological capabilities (Henderson & Clark, 1990; Leonard-Barton, 1992; Tushman & Anderson, 1986) and managerial cognition (Ding, 2011; Kaplan & Tripsas, 2008; Leonard-Barton & Deschamps, 1988) influence firm level responses to technological changes. Yet, ambiguity exists concerning the role of capabilities and cognition in decision making during the early stage of industry emergence. Resolving this ambiguity is necessary as it can help us to better understand the performance consequences of firms’ innovation decisions.

Research on technological capability and managerial cognition has developed in two parallel tracks (Eggers & Kaplan, 2013). Capability research argues that heterogeneous capability endowments explain variations in innovation performance (Ahuja & Lampert, 2001; Cohen & Levinthal, 1990; Zhou & Wu, 2010). Technological resources are prioritized at the expense of managers, who are assumed to have accurate mental representations of their firms’ capabilities (Eggers & Kaplan, 2013) and interpret external changes in similar ways. A different body of literature draws from the upper echelons theory and emphasizes the role of managers. This perspective suggests that “organizational outcomes – both strategies and effectiveness – are

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2 This paper was developed in collaboration with Dr. Devi Gnyawali
viewed as reflections of the values and cognitive bases of powerful actors in the organization” (Hambrick & Mason, 1984: 193). Firm level capabilities are largely overlooked as researchers use managerial demographics as proxies for their values and cognitive bases (Hambrick, 2007). Characteristics such as age, tenure, education, and functional background are shown to predict the firm’s innovation decisions and outcomes (Alexiev et al, 2010; Bantel & Jackson, 1989; Talke et al, 2010).

These insights highlight the significance of capabilities and cognition, but it is unclear how they matter during industry emergence. Further, as these literatures have developed independently of one another, it is unclear how capability and cognition work separately and together to influence firm innovation in the context of industry emergence. Specifically, their role in influencing choices between product and application based innovations is poorly understood. This knowledge is highly relevant where capability and cognition can potentially lead to different decisions and trajectories during the emergent and uncertain process of new industry emergence. Therefore, we ask: how do technological capability and managerial background characteristics independently and interactively shape firms’ innovation choices in emerging industries? We argue that a firm’s existing technological capability provides resources that managers can utilize to achieve innovative outcomes during industry emergence (Kaplan & Tripsas, 2008; Tripsas, 2009). Similarly, managerial characteristics shape how they mentally represent the firm’s capabilities (Kunc & Morecroft, 2010). Thus, we theorize that managers make innovation choices based on their perceptions of opportunities and challenges and mental representations of what the firm is capable of accomplishing (Eggers & Kaplan, 2013; Kaplan, 2008; Kaplan & Tripsas, 2008). We test these independent and joint effects in the small satellite
industry. This sector has experienced rapid evolution and growth since the introduction of CubeSats, small, low cost satellites that are easy to build and launch.

This study contributes to the literature in several ways. First, with a focus on an intriguing emerging industry context, we offer insights regarding how firms make innovation choices, which are important antecedents of innovation performance (Kaplinsky, 2000; Talke et al, 2010). Innovation is crucial for firm survival and growth in nascent industries (Santos & Eisenhardt, 2009) and firms have different options to pursue innovations. Our research explicates two major innovation options—product and application based innovations—and determinants of such options. Second, we demonstrate that different aspects of technological capability have different outcomes for product and application innovations. For example, technological relatedness contributes to product innovation but hurts application innovation whereas technological diversity produces opposite effects. This highlights the importance of a fine-grained understanding of technological capability to understand innovation choices in an emerging industry context. Third, our results show that CEO's backgrounds seem to matter differently for product and application based innovations. CEOs with more experience in related industries are associated with more product innovations whereas CEOs with experience in more diverse range of industries are associated with more applications innovations. We provide comparisons of the distinct effects of capability and cognition and illustrate the significance of each when facing technological changes. Our findings underscore the need to examine the role of technological capabilities and managerial cognition in a more fine-grained manner. Finally, our findings about the significant interaction effects between firm capability and CEO experience underscore the importance of simultaneously considering these two drivers of innovation choices and provide integrative and holistic insights.
3.2 THE ROLE OF TECHNOLOGICAL CAPABILITY AND MANAGERS

Technological Capability

Literature on technological capability has mainly used heterogeneity in firms’ technological resources to explain performance differences (Helfat, 1997; Lee et al., 2001; McEvily & Chakravarthy, 2002; Song, Droge, Hanvanich, & Calantone, 2005). Scholars have shown that the strength (Dushnitsky & Lenox, 2005a; Srivastava & Gnyawali, 2011), complementarity (Makri, Hitt, & Lane, 2010; Wu, Wan, & Levinthal, 2014), similarity (Speckbacher, Neumann, & Hoffmann, 2015), complexity (McEvily & Chakravarthy, 2002), and diversity (Quintana-Garcia & Benavides-Velasco, 2008) of firms’ technological knowledge are important predictors of development of dynamic capabilities, diversification and investment decisions, new product introduction, and other performance outcomes. Among the various factors related to technological capability, technological diversity and technological relatedness are two of the most widely examined characteristics when predicting innovation outcomes (Schildt et al., 2012). Technological diversity refers to the range or breadth of technologies possessed by a firm (Patel & Pavitt, 1997; Srivastava & Gnyawali, 2011). It describes whether a firm focuses on developing a narrow or a broad range of technologies (Argyres, 1996). Technological relatedness, defined here as the extent to which a firm’s knowledge base and the emerging industry knowledge base cover similar technology domains (Frankort, 2016; Lane & Lubatkin, 1998), reflects the degree to which their technological problem solving focuses on the same narrowly defined areas of knowledge (Makri et al., 2010). Both elements become particularly relevant in predicting innovation requiring knowledge that is novel and distant to a firm’s existing knowledge base (Nooteboom et al, 2007).
Even with commonly shared definitions and measures, the effects of technological relatedness and diversify are diverse and inconsistent in the existing literature. Technological diversity as a central determinant of absorptive capacity (Cohen & Levinthal, 1990; Schildt et al., 2012) increases firms’ awareness of new opportunities and helps firms to capture more technological possibilities. Studies have shown that diversity facilitates knowledge transfer (Schildt et al., 2012) and increases firms’ competence to innovate (Quintana-García & Benavides-Velasco, 2008). However, others have demonstrated that technologically diverse firms may be less willing to leverage diverse external knowledge as it is more challenging to simultaneously explore diverse knowledge both internally and externally (Srivastava & Gnyawali, 2011). Technological diverse firms may not possess enough technological expertise even when they are willing to utilize more external knowledge (Vasudeva & Anand, 2011). This may explain reductions in the firm’s ability to benefit from geographically distributed R&D (Lahiri, 2010) and decreased breakthrough innovations when external knowledge is also diverse (Srivastava & Gnyawali, 2011). Technological relatedness on the other hand increases the likelihood of having foundational knowledge necessary for learning (Lane & Lubatkin, 1998), but it is not significantly beneficial for rapidly identifying and transferring external knowledge (Schildt et al., 2012). The overall effects of technological relatedness on invention quantity, quality, and novelty could be positive, negative or not significant (Makri et al., 2010). These diverse and inconsistent findings call for more fine-grained scrutiny of these two knowledge characteristics.

We suggest that the diverse effects of firm’s technology capabilities can be better understood when we examine the role of managers. We proceed to incorporate cognition research, which suggests that how managers perceive and interpret the external environment
influences the firm’s strategic decisions and performance (Barr et al, 1992; Narayanan et al, 
2011; Tripsas & Gavetti, 2000). Accordingly, we develop hypotheses about the main effects of 
technological capability and cognition before proposing interaction effects.

Managerial Cognition

Theorists from the Carnegie School argue that decision makers have bounded rationality 
and cognitive limitations (Cyert & March, 1963; March & Simon, 1958). Therefore, complex 
decisions are often not the outcomes of a mechanical quest for the economic optimization of 
resources (Cyert & March, 1963; March & Simon, 1958). Instead, behavioral factors play 
significant roles. Upper echelons theory states that characteristics of decision makers are vital 
 sources of heterogeneous strategic choices as “each decision maker brings his or her set of 
“givens” to an administrative situation” (Hambrick & Mason, 1984: 194). Organizational 
decisions, such as a firm’s innovation choices, may be viewed as “reflections of values and 
cognitive bases of powerful actors in the organization” (Hambrick & Mason, 1984: 193).

Innovation choices are complex strategic decisions. Behavioral theory suggests that 
optimizing the firm’s technological resources is certainly not the only important factor. The 
“givens” (March & Simon, 1958) brought by the powerful actor in this situation – oftentimes, the 
firm’s CEO – also directly influence the firm’s innovation focus. Such “givens” filter and distort 
the CEO’s perception of the external environment and the firm’s internal resource endowment, 
thereby influencing innovation decisions (Garg et al, 2003 Hambrick & Mason, 1984). When 
facing the same external environment, different CEOs use different filters to make “scanning 
selections” – they can only see part of the environment. CEOs have limited field of vision 
(Hambrick & Mason, 1984) and end up having different strategic emphasis (Garg et al, 2003). 
As well as removing information, these “givens” also distort the information CEOs pay attention
to. Lefebvre and colleagues (1993) argue that a “prism effect” means that the CEO’s perception is often a distorted version of the objective reality. In this case, the prism is the “givens” brought by the CEO.

While “givens” play important roles in influencing a firm’s innovation decision, it is unclear how they can be empirically studied. Upper echelons theory suggests that they are reflected in decision makers’ cognitive bases and values, (their knowledge about future alternatives, and consequences, and their preferences of different alternatives) (Hambrick & Mason, 1984). Since the cognitive bases and values of managers are difficult to observe, theorists suggest that “demographic characteristics of executive can be used as valid, albeit incomplete and imprecise, proxies of executives’ cognitive frames” (Hambrick, 2007: 335). By building on these insights, we argue that CEOs’ work experiences shape both their cognitive bases and values. Therefore, among the various observable managerial characteristics that have been highlighted in the upper echelons perspective (Carpenter et al, 2004; Hambrick & Mason, 1984; Hambrick, 2007), as a start, in this study, we explore how a CEO’s work experience shapes innovation decisions. We also examine how it works in tandem with firm level technological capabilities to influence the firm’s innovation choices.

Literature suggests that upper echelons theory is most useful in predicting choices when managers have more discretion (Hambrick, 2007; Hambrick & Finkelstein, 1987) and are in demanding roles (Hambrick et al, 2005). In small entrepreneurial firms, where the top management team is frequently evolving, CEOs may have a great deal of discretion and experience heavy job demands in making innovation choices. CEOs in such firms are more likely to take mental shortcuts and “fall back on what they have tried or seen work in the past” (Hambrick, 2007: 336). Therefore, innovation choices may be influenced by the CEO’s prior
experiences. We examine if CEOs’ diverse or related industry experience can explain firms’ innovation choices.

### 3.3 THEORY AND HYPOTHESES

We briefly discuss key features of an emerging industry context and firms’ choices of product versus application innovations before articulating the logic for the hypotheses.

**Emerging Industry and Product Innovation versus Application Innovation**

We argue that when creating innovations in an emerging industry, entrepreneurial firms can focus on creating and improving the existing core products in this industry (Hunt, 2013), or they could find novel applications of the emerging technology. During industry emergence, ambiguities exist concerning (1) what are the new technological designs in the industry and what are their key constituting components (Grodal et al., 2015; Santos & Eisenhardt, 2009; Tushman & Anderson, 1986) and (2) how the new designs can be applied (Darr & Talmud, 2003). Even though these are interrelated questions, and firms should keep both questions in mind when they create innovations in an emerging industry, oftentimes, firms are likely to focus on different parts of these questions. For example, in the emerging 3D printing industry, firms like Markforged or XJET have focused on improving printing speed or finding stronger composite materials and innovated by providing state-of-the-art 3D printers. To the contrary, firms like Body Labs have innovated by finding novel applications for 3D printers, including health and fitness, where they are used to scan the human body.

Studies of new industry emergence focus on outcomes such as new technological designs (Henderson & Clark, 1990), new schemas (Bingham & Kahl, 2013), and new categories (Grodal et al, 2015; Navis & Glynn, 2010). Research either examines the constituent components or the linking mechanisms that connect different components. Definitions of these two elements are
similar to definitions of component versus architectural innovation (Henderson & Clark, 1990). Architectural innovations are “innovations that change the way in which the components of a product are linked together, while leaving the core design concepts (and thus the basic knowledge underlying the components) untouched” (Henderson and Clark, 1990: 10). Within a product, a component is defined as “physically distinct portion of the product that embodies a core design concept and performs a well-defined function” (Henderson & Clark, 1990:11). While most of the architectural innovation discussion is focused on specific products and employs analysis at two levels, we argue that in the context of new industry emergence, there are three different levels of components versus architectures: (1) the components of each product design, (2) mechanisms that link different components to a product, and (3) mechanisms that link the products to different areas of applications. Our paper uses the first two as emerging industry product innovation, and the third as emerging industry application innovation.

The distinction between product innovation and application innovation in an emerging industry is important because the initial product designs in an emerging industry usually have very limited applications. New entrants discovering novel applications significantly drive industry development (Von Hippel, 1998). Firm often use design recombination, which is “the creative synthesis of two or more previously separate designs that results in the creation of a new design to address an existing or potential need” (Grodal et al, 2015), to create innovations. Innovations are often proposed not by producers but by users (Riggs & Von Hippel, 1994). In the industry context of this study, for example, CubeSats – small satellites that are made up of multiples of $10 \times 10 \times 11.35$ cm cubic units – were introduced by professors from Stanford and Caltech primarily for low cost space science research and experiments. The industry started to grow as firms explored ways in which CubeSats, which are low cost, easy to build, and easy to
launch compared to larger satellites, could be used for other purposes such as earth observations, internet services, and big data processing. In addition, just as successful product development requires both component knowledge and architectural knowledge (Henderson & Clark, 1990), successful industry development involves two distinct types of knowledge: product technology and product application (ways in which the products could be used in other areas).

We propose that technological capabilities and CEO experiences both independently and interactively shape the firm’s innovation choices. Figure 3-1 depicts the conceptual model and core logic for the various effects.

[Insert Figure 3-1 about here]

**Technological Relatedness and Firm Innovation Choices**

Technological relatedness, defined as the extent to which the firm’s technologies overlap with available technologies in the emerging industry, provides a set of benefits for firms innovating in emerging industries. First, technological relatedness increases the speed of learning new emerging technologies. The concept of relative absorptive capacity suggests that a firm’s ability to leverage knowledge from an external source depends on the level of similarity of the firm’s knowledge with the source (Lane & Lubatkin, 1998). Firms operating in similar technological domains are likely to experience similar “know whats” (the challenges associated with the particular technological domain) and “know hows” (the casual linkage of the particular domain to other domains) (Lubatkin, Florin, & Lane, 2001). Firms learn faster when they have shared understandings of key technological challenges in an emerging industry and available resolutions. Second, technologically related firms usually have more things to learn from the emerging industry, and if they learn, they can derive more direct and immediate benefits from existing technological offerings (Schildt et al, 2012). As they are tackling similar problems,
technologies from the emerging industry may offer relevant solutions in other areas (Lane & Lubatkin, 1998; Makri et al., 2010) and provide immediate returns once the problem is solved.

There are also disadvantages associated with technological relatedness. Firms focusing on similar technological domains are more likely to have dismissive attitudes towards emerging technologies that are new and distant to their existing knowledge domains (Ahuja & Lampert, 2001; Gavetti, 2012). The value of the emerging technology may be underestimated and there are fewer. Additionally, technological similarity provides less combinative opportunities if all the elements are from the similar domains (Galunic & Rodan, 1998; Kogut & Zander, 1992).

The advantages of technological relatedness may be amplified when firms introduce new product innovations in an emerging industry. Technologically related firms can understand and learn the new industry technologies faster, and have more opportunities to use their existing expertise to introduce new products in related domains (Garcia & Calantone, 2002). The disadvantages of technological similarity are reduced when firms choose to create new product innovations in emerging industries. Despite emerging industries being cognitively distant, firms have fewer problems noticing and identifying novel knowledge from related technological domains. On the other hand, technological relatedness is less relevant for application based innovations. When firms choose application based innovations, technological relatedness offers less distinct knowledge elements that can facilitate new combinations and novel purposes of applications. The learning advantages surrounding deep industry expertise that are important for product innovations are less valuable. Firms do not need to develop deep industry specific knowledge to find new areas of application. Where application based innovations are removed from the firm’s existing technological trajectory, they may even hurt their existing product performance (Tripsas, 2009). Therefore, we propose the following hypothesis:
H1a: In emerging industries, technologically related firms are more likely to pursue product innovation than application innovation.

Technological Diversity and Firm Innovation Choices

Technological diversity has several important implications for innovation. A broader range of internal technologies increases the likelihood of identifying valuable new external knowledge, especially in uncertain external environments. As emphasized by Cohen & Levinthal (1990: 131): “In a setting in which there is uncertainty about the knowledge domain from which potentially useful information may emerge, a diverse background provides a more robust basis for learning because it increases the prospect that incoming information will relate to what is already known”. Breadth in firms’ “inventories of competencies” (March & Levinthal, 1993) facilitates acceptance and internalization of novel ideas from the external environment. Firms with a diverse technological base are more open to emerging ideas originating from outside the firm (Quintana-García & Benavides-Velasco, 2008), and are likely to have employees that are accustomed to collaborating with others from different technological backgrounds (Østergaard et al, 2011). Yet, technologically diverse firms may not possess sufficient expertise to efficiently absorb the new knowledge. They may take more time to build competencies required for complex technological inventions using a particular emerging technology (Schildt et al., 2012). Furthermore, technologically diverse firms may already have enough combinative opportunities internally and thus are less likely to pursue new external opportunities, especially when external opportunities are more risky (Srivastava & Gnyawali, 2011).

We argue that when firms create innovations by introducing new products in an emerging industry, they need more industry specific knowledge (Balasubramanian, 2011). The benefits provided by technological diversity – superior capabilities to identify and accept new knowledge – are not enough to generate the expertise required for developing industry-specific products.
These challenges are amplified where technologically diverse firms are less motivated to devote resources to developing such expertise. Therefore, we argue that technologically diversified firms are less likely to pursue new product innovations in an emerging industry. However, application based innovations require less industry-specific knowledge but more combinative capabilities. Technologically diverse firms have more distinct knowledge elements that can be used for combination. Deep understanding of underlying technologies is not required for application based innovations. This motivates technologically diverse firms to explore application based opportunities from emerging industries. Therefore, we propose the following hypothesis:

*H1b: In emerging industries, technologically diversified firms are more likely to pursue application innovation than product innovation.*

**CEOs Background and Firm Innovation Choices**

We now develop hypotheses concerning the influence of CEO’s industry experience on the firm’s innovation choices. The logic is as follow: CEO’s industry experience will shape his/her cognitive base and values. These serve as “givens” that the CEOs bring with them when they make innovation decisions (Hambrick & Mason, 1984). As outlined, “givens” filter and distort perceptions of opportunities and challenges in the emerging industry, thus influencing the decisions. We focus on the influence of the CEO’s industry experience on their perception of the *external environment*. When we develop arguments about interaction between CEO experience and internal capabilities, we theorize how CEOs’ industry experience shapes their perception of both the *internal and external* environment and their decisions.

We argue that, if CEOs have more related industry work experience (if they have worked in related industries for a significant period of time (Tian et al, 2011)), they are more likely to accumulate industry-specific knowledge concerning key products on the market, their
technological features and potential shortcomings (Junkunc & Eckhardt, 2009). This contributes to knowledge concerning how new products are built. CEOs with related industry experience understand what the key components, relevant architecture, and key technical challenges. When they scan information from the external environment – the new emerging industry, they are more likely to pay attention to information that is related to the firm’s existing line of products. They may be aware of technologies that advance, add to, or challenge their existing products. As noted by one of satellite industry CEOs: “I have been an aerospace engineer for more than 30 years, and we see there are still a lot of areas that we could improve to build a better satellite”. This CEO’s related knowledge base helps him to search for more industry-specific new product information while filtering less relevant information.

CEOs’ industry experiences also shape their values and distort the information they pay attention to. CEOs with more industry related experience may have greater psychological commitment to the status quo (Alutto & Hrebiniak, 1975; Bantel, 1989; Staw & Ross, 1980). When facing innovation choices, they will prioritize the option that maintains the firm’s current position. Application innovations often redefine an industry’s boundary and bring more changes to the firm’s industry position. Thus, they are more likely to be resisted by CEOs with more industry experience. It is possible that focusing on downstream activities of an industry value chain can generate higher profit margins, but CEOs with more industry related experience may dismiss the value of application innovation. They are more likely to perceive application innovation as irrelevant to existing lines of business and prioritize product innovation. Therefore:

\[ H2a: \text{In emerging industries, CEOs with more related industry work experience are more likely to pursue product innovation than application innovation.} \]

CEO industry experience diversity, the range or breadth of industries that the CEO has worked in before joining the firm (Tian et al, 2011), on the other hand, may decrease the
likelihood they will pursue product innovations. CEOs who have worked in different industries often have a more diverse knowledge base and are less likely to have a technical expertise in the current industry. Yet, CEOs’ jobs have a considerable amount of general human capital (Murphy & Zábojnik, 2004). By serving as CEOs in different industries, they have more knowledge on different industry structures and how to manage firms in different parts of the industry value chain. With this diverse knowledge, they periphery areas to gather industry information. They are more likely to see how the entire industry works, but the technological advancements of specific products may be filtered out. Industry-specific experience is difficult to transfer between employers (Groysberg et al., 2008; Groysberg & Lee, 2009; Hamori & Koyuncu, 2015) and CEOs are less likely to have the knowledge base and mental capacity to fully appreciate technological details.

CEOs with more diverse industry experience are more likely to have different value preferences when they make innovation choices. Their diverse work industry work experience suggests that they prefer change. As application innovation often reshapes the structure of the entire industry and requires more changes than product innovation, CEOs with more diverse experience are more likely to prioritize application innovation. Their perceptions of technological advancement in the emerging industry are more likely to position technologies as tools, but not the end product. As one CEO we interviewed highlighted, “what is so fascinating about this industry are not only the technologies themselves, but also how you can use these satellites in so many different areas. The data they provide is much better in value”. The space expert CEO sees satellite technologies as the key to industry development, but the professional CEO sees more value in the data satellites provide. Therefore,

\[ H2b: \text{In emerging industries, CEOs with more diverse industry work experience are more likely to pursue application innovation than product innovation.} \]
Joint Effects of Technological Capability and CEO Experience

In this section, we develop hypotheses concerning how CEO experience interacts with technological capability in influencing firm’s innovation choices. As argued in the previous sections, if both technological capabilities and CEO’s experience are highly related to the emerging industry, then the firm is more likely to pursue product innovation. On the opposite side, if both resource and CEO experience are diverse, then application innovation may be preferred. However, when firm level technological capabilities are not aligned with the CEO’s experience, the interactions become more interesting. We proceed to examine how firms make innovation choices if they have related technological resources but the CEO has a diverse background, or if firms have diverse technological resources but the CEO has related industry work experience.

CEO’s industry work experience not only influences their perception of the external information, it also affects how CEOs perceive and interpret the internal environment (Garg et al, 2003). In a firm with more technologically related resources, a CEO with diverse industry experience may pay less attention to details of the firm’s technological advantage. Instead, the CEO is more likely to view these related resources as tools to apply these technologies in new areas. CEOs with diverse experience may also lead the firm to overcome its rigidity and be more open to explore other industry domains. Therefore, even though technologically related firms are more likely to pursue product innovation, if they have CEOs with diverse experience, then the likelihood of pursuing product innovation will be reduced.

H3a: CEO experience diversity negatively moderates the relationship between technological relatedness and firm’s likelihood of having product innovation.
On the other hand, if the firm has a diverse set of technological resources, yet the CEO has related industry experience, he or she may pay more attention to the firm’s capabilities that are related to the focal products of the industry and pay less attention to unrelated resources. The CEO may put less value on resource diversity and prioritize related resources are the development of further related resources. Even though technological resource diversity may independently increase the likelihood of application innovation, we argue that a CEO with more related industry experience will reduce the likelihood of application innovation.

\[ H3b: \text{CEO experience relatedness negatively moderates the relationship between technological diversity and firm’s likelihood of having application innovation.} \]

3.4 METHODS

Research context

We test our model in the small satellite industry. The small satellite industry emerged with the introduction of CubeSats in 1999, significantly reducing the cost of launching satellites. The CubeSat was first developed by university professors to provide opportunities to use satellite technologies for space related scientific research. Since then, the small satellite industry has seen tremendous growth in terms of technological development as well as satellite production and deployment.

Historically, the first few satellites were developed and launched by government agencies and the first wave of satellite development is largely driven by the space race between the United States and the Soviet Union during the cold war. After the initial launches, traditional satellite manufacturers focused on developing larger launch vehicles with large payload capabilities (Helvajian & Jason, 2009). In this environment, CubeSat, a member of the small satellite family, was a radical innovation that advances the price/performance frontier by much more than the existing rate of progress (Gatignon et al, 2006). A basic CubeSat unit is made up of multiple of
10*10*10 cm cubic unit. CubeSats have a maximum mass of 1.33 kilograms. The small size and light weight features of small satellites significantly reduces the launch cost to around $40,000. Small satellites have a maximum weight of 500 kilograms. They include small satellite (100-500kg), microsatellites (10-100 kg), nanosatellite (1-10 kg), picosatellites (0.1-1 kg), and chipsat (10-100g). Figure 3-2 illustrates the historic evolution of the small satellite industry.

The small satellite industry has grown rapidly in the past decade. Beginning in 2014, more than 50% of satellites are launched for commercial use. The percentage of military, civil, and government satellites has been decreasing (Spaceworks Market Observation Report) and more than 50% of the payloads launched are nano and microsatellites. Average satellite mass has decreased 30% from 2013 to 2014. The rapid growth of the industry has also attracted a large number of new entrants. NewSpace Global, a company that tracks the development of the small satellite industry and provides financially focused analysis of commercial space firms, show that currently around 1,000 for-profit companies are seeking to commercialize space, and a large number of them have focused on small satellites.

There are four main segments in the small satellites industry: satellite manufacturers, launch vehicle and service providers, ground equipment, and satellites services. All satellites have two principal subsystems: the platform and the payload. The platform is the basic frame of the satellite and the components which allow it to function in space. It is not related to the satellite’s mission. The control segment of the ground equipment controls these components. The platform consists of the following components: structure of the satellite, power, propulsion, stabilization and attitude control, thermal control, environmental control, telemetry, tracking and common subsystems. The function and capabilities of the payload describe the reasons a satellite
is placed in orbit. The payload provides spaced based capabilities to the users. The general types of satellite payload systems are: communications, position/navigation, reconnaissance, surveillance and target acquisition, weather and environment monitoring, scientific experiments, and manned missions.

The small satellite industry provides an ideal context to study how firms respond differently to technological changes in an emerging industry. First, there are an abundance of opportunities for firms to pursue product and application innovations. While small satellites have started to challenge the use of traditional large satellites, the design of small satellites and subsystems, ground equipment, and launch vehicles are still immature and require further development. Second, a diverse set of players exist in the current nascent stage of the industry. Incumbents such as Space System Loral and Lockheed Martin produce traditional large satellites for primarily defense and military uses; while diversifying entrants such as Facebook or Google are trying to find novel applications of this new technology within their existing product or services; and start-up firms like O3b Networks and Planet Labs are attempting disruptive innovations. Third, diverse players bring idiosyncratic technological capabilities (illustrated by a multitude of technological designs) and managerial experience into this emerging industry.

**Data Sources**

To obtain a list of firms operating in the small satellite industry, we used a database developed by NewSpace Global that provides information on both public and private firms operating in the small satellite industry. The database provides basic information including company founding year, location, industry segments, firm size, their estimated revenue, and NewSpace Global’s rating of each firm based on its management team, market assessment, financial situation and technology development. We confirmed with multiple executives in the
small satellite industry that this database is widely used, and that they believe the information it provides is accurate, and the ratings are fair. We used NewSpace Global’s news database and other space industry focused news websites such as Spacenews.com, Aviationweek.com, and Satnews.com to collect information on firm’s new product/service introduction and product/service descriptions.

Since the small satellite industry is a global industry with many firms operating outside the United States, we collected patent information of each firm from the World Intellectual Property Organization’s PatentScope base. This database provides more complete information of patent for international firms. To gather data on CEO’s background characteristics, we searched LinkedIn.com, company websites, and Bloomberg.com to gather information on the CEO’s background and work experience. After removing firms with missing data, our final sample incorporated full information for 196.

Measurements

*Dependent Variable: product or application innovation.* Drawing from the measures of architecture versus component innovation, we measured product innovations as innovations that focus on distinct products of the satellite industry that “embodies a core design concept and performs a well-defined function” (Henderson & Clark, 1990: 11). On the other hand, application innovations focus on innovations that change the way in which satellite products and other industry products are linked together, while leaving the core design concepts of satellite products untouched (Henderson & Clark, 1990). We measured the dependent variable product innovation versus application innovation using dummy variables indicating that the firm has either introduced a new product that focuses on small satellite components, system integration, ground equipment or control system, launch systems, or applied small satellite technologies to
other areas. For example, OneWeb created innovations by introducing new high-speed Internet connection service using small satellite constellations. OneWeb innovated by creating new linkages between small satellites and the Internet service. This innovation did not change any core design concepts of the satellites, but it created new ways to use small satellites. We coded this innovation as application innovation. On the other hand, products like ArduSat1 and ArduSatX, developed by Spire, are product innovations – they improved the performance of small satellites by utilizing Audrino boards as the core of the avionics system without changing the existing functions of satellite or creating any new linkages between satellites and other application areas. We coded this example as product innovation. More examples of product versus application innovation are shown in Table 3-1.

Independent Variable. Following previous studies, we measured the independent variable technological diversity using the Herfindahl index, which is calculated as $1 - \sum_{i=1}^{K} s_i^2$ (Lahiri, 2010; Quintana-Garcia & Benavides-Velasco, 2007; Schildt et al, 2012). $s_i$ represents the share of patents in four-digit class i, and k represents the number of different patent classes the firm has filed patent for. The minimum value of 0 represents a firm that has all of its patents filed in the same patent class, and the maximum value of 1 represents a firm that has every patent filed in a distinct class.

Technological relatedness is measured as the overlap of a focal company’s patents with those of emerging technologies in terms of patent classes $= \frac{\sum_{i=1}^{K} \sqrt{c_{k,A} \cdot c_{k,B}}}{\sqrt{\text{Patents}_A \cdot \text{Patents}_B}}$ (Frankort, 2016; Schildt et al, 2012). We multiplied the number of patents in patent classes (k) for companies A and small satellite related classes B, summed up the results from every patent class, and then divided the result by the geometric mean of patent portfolio sizes. To identify satellite related
patent classes, we followed Yayavaram & Ahuja (2008) and Carnabuci & Operti (2013) and considered the four-digit classes that were assigned to all of the patents of key satellite firms in the sample. Then we ranked these classes based on the number of patents in each class and the number of firms that had patents assigned to them. We considered the top 50 classes to be the satellite classes and calculated the relatedness measure based on the top 50 classes. To illustrate what are the key capabilities in developing satellite technologies, we selectively listed of the top 10 patent classes in Table 3-2.

[Insert Table 3-2 about here]

CEO experience relatedness is measured as the number of years the CEO of the firm has worked in the space and aviation industry divided by the total number of years this CEO has ever worked. CEO experience diversity is measured as the number of different industries the CEO has worked in prior to joining the firm. For each firm the CEO has work experience with, LinkedIn has its industry classification. We use the industry classification from LinkedIn to identify the number of different industries.

We also include control variables including basic information such as firm age, firm size (average number of employees), and geographic location (headquarters in North America, Asia, or Europe). Performance variables, such as the average estimated revenue of the firm, are also included. NewSpace Global provides its own ranking of all the firms listed in the database based on their investment potential, which we also included as a control variable. NewSpace Global provides its own ratings (from 1-10) in four areas of each firm: market, capitalization, technology, and management team. As these may influence innovation choices, they were also included. Table 3-3 provides descriptive statistics and definitions for each variable.

[Insert Table 3-3 about here]
3.5 RESULTS

Correlation and descriptive statistics of key variables are shown in 3-4. We examined the variance inflation factor and did not find evidence of possible multicollinearity. Since the dependent variable is binary, we use a logit regression model. We also run the analysis using a probit model and obtain similar results. Results of our logit regression analysis are shown in Table 3-5.

[Insert Table 3-4 and 3-5 about here]

In Table 3-5, Model 1 contains all control variables; Models 2 and 3 tests for the explanatory power of technological capability (H1a and H1b); Models 4 and 5 add the effects of CEO experience (H2a and H2b); Models 6 and 7 additionally show the hypothesized interaction effects (H3a and H3b). With regard to the goodness-of-fit statistics, the chi-square estimates associated with all models are highly significant (p<0.05 for Model 1, and p<0.001 for Model 2-7). The pseudo $R^2$ also shows that each subsequent model is significantly better than the preceding model.

Model 1 shows the effect of control variables on firms’ innovation choices. We found that a firm’s capitalization rating is negatively related to its likelihood of pursuing product innovation (-0.465, p<0.1), and a firm’s technological rating is positively related to its likelihood of pursuing product innovation (0.473, p<0.1). It is likely that firms with more financial resources could take more risk to experiment with application innovation, and firms with stronger technological resources have more technological ingredients for them to pursue product innovation.

Model 2 tests the direct effect of technological relatedness. As hypothesized, technological relatedness is positively related to the likelihood of pursuing production innovation.
(3.408, p<0.05). Its effect is consistent across Model 2-5, thus supporting Hypothesis 1a. Model 3 tests the relationship between technological diversity and a firm’s likelihood of pursuing application innovation. We hypothesized a positive relationship between technological diversity and application innovation. While the sign of the coefficient is positive, it is not statistically significant (0.105, p>0.10). Therefore, we did not find support for hypothesis 1b.

Model 4 tests the effect of CEO industry experience relatedness. In hypotheses 2a, we propose that CEOs with more related industry experience are more likely to pursue product innovation. Results in Model 4 supports this hypothesis (1.259, p<0.01). In hypotheses 2b, we argued that CEOs with more diverse industry experience are more likely to pursue application innovation. Results in Model 5 support the hypothesis (0.521, p<0.01).

Models 6 and 7 examine the interactions between technological resources and CEO experience. We argued that CEO industry experience negatively moderates the relationship between technological relatedness and a firm’s likelihood of pursuing product innovation. Yet, as shown in Model 6, the coefficient for the interaction term is not in the predicted sign (1.737, p>0.1). Figure 3-3 illustrates the moderating effect of CEO experience diversity on the relationship between technology relatedness and product innovation. As shown, compared to CEOs who have only worked in one industry, CEOs who have worked in five different industries are less likely to pursue product innovation. Yet, the difference in CEOs’ work experience diversity does not change the slope between technology relatedness and the likelihood of pursuing product application. Therefore, hypothesis 3a is not supported. Lastly, Model 7 tests the moderating effect of CEO experience relatedness. As shown in the model, CEO experience relatedness negatively moderates the relationship between technological diversity and application innovation (-1.490, p<0.05). Figure 3-4 illustrates the moderating effect of CEO
experience relatedness on the relationship between technology diversity and application innovation. As shown, for CEOs who have no work experience in the space industry, technology diversity increases their likelihood of pursuing application innovation. Yet, for CEOs who have 10 years of work experience in the space industry, having more technology diversity decreases their likelihood of pursuing application innovation. CEO experience relatedness negatively moderates the relationship between technology diversity and the likelihood of pursuing application innovation. Therefore, we did find support for hypothesis 3b.

[Insert Figure 3-3 and 3-4 about here]

Overall, the results show that technological relatedness has a strong positive effect on product innovation (Models 2-5). Yet, this positive relationship becomes non-significant when the interaction term of CEO experience is added (Model 6-7). We did not find a significant effect of technological diversity on application innovation. On the CEO experience side, results showed that CEOs with more related experience are indeed more likely to pursue product innovation (Model 4-6), but after adding the interaction term, the independent effect of CEO related experience becomes non-significant. CEO experience diversity showed a consistent positive effect on application innovation, even after adding the interaction term (Model 5-7). CEOs’ related experience reduces technologically diverse firms’ likelihood of pursuing application innovation.

### 3.6 CONTRIBUTIONS AND IMPLICATIONS

This paper examines how a firm’s technological capability and managerial cognition (inferred from CEO experience) influence the firm’s likelihood of making innovation choices in terms of product versus application innovations. While research has shown that technological capabilities and managerial cognition matter, the influence of these aspects has not been
examined in the context of innovation choices in an emerging industry context. Moreover, research in capability and cognition has emerged in two separate streams, and limited attempts have been made to examine how capability and cognition jointly or interactively influence innovation choices. We theorize that a firm’s existing technological capability provides resources (or ingredients, tools) managers could deploy to innovate in the emerging industry (Kaplan & Tripsas, 2008; Tripsas, 2009). Further, we suggest that managerial background characteristics shape how managers perceive opportunities and challenges in the external environment and how the managers mentally represent their firms’ existing capabilities (Kunc & Morecroft, 2010). Managers make innovation choices in the emerging industry through their perceptions of the opportunities and challenges in the emerging industry and through their mental representation of what the firm is currently capable of doing (Eggers & Kaplan, 2013; Kaplan, 2008b; Kaplan & Tripsas, 2008). We tested hypotheses in the small satellite industry, which has substantially grown in terms of development, launch, and uses of small satellites since the introduction of CubeSat in 1999.

**Contributions**

This study contributes to the literature by examining the role of technological capability and cognition in shaping innovation choices in the context of an emerging industry. We integrate insights from previously independent literature streams to provide a more holistic understanding while our paper also helps to compare the distinct effects of technological capability and CEO experience. We briefly discuss key contributions.

First, the results of this study provide comparisons between the distinct effects of technological resource and CEO experience. This helps to explain which aspect is more important when facing technological changes. Results show that while having related technology
is more important for product innovation, having a CEO with more diverse experience is more important for application innovation. It is likely that firms may not be able to pursue product innovation if they don’t have the necessary technological ingredients. However, the pursuit of application innovation is determined more strongly by the CEO’s experience, which shapes the mindset and vision for the firm.

Second, this study offers insights on how firms make innovation choices, particularly in an emerging industry context. Innovation choices are important antecedents of firm’s innovation performance (Ralke et al, 2010). We believe the distinction between product versus application innovation is novel and meaningful. The growth of emerging industries is often driven by broad application of core products. As the technology can be used and applied in many different areas, it generates growth potential and attracts more firms to enter into the emerging industry. This study offers insights on determinants of decisions concerning product versus application innovation. As illustrated, technological relatedness may be the main driver of product innovation, and CEOs with diverse industry experience a key driver of application innovation. By identifying the antecedents of firm’s innovation choices, we extend our understanding of antecedents of innovation choices and, potentially, innovation performance.

Finally, we explicitly examine how technological capability and managerial interpretation interactively shape innovation choices. We integrate findings from previously separated literature streams and provide a more holistic understanding. Our findings show that while technological relatedness may have a positive effect on product innovation, it becomes non-significant when the interaction between CEO experience and technological relatedness is considered. Results show that even though firms with related technologies are more likely to pursue product innovation, if the CEO has more diverse experience, the advantages of
technological relatedness become less important. We offer similar findings regarding CEO related experience. If the CEO has more industry related work experience, the firm is more likely to pursue product innovation. Nonetheless, if the CEO works for a firm with a diverse set of technological capabilities, his or her industry related experience becomes less significant. The significance of the interaction terms and the non-significance of the individual terms demonstrate the importance of taking both firm resource and CEO experience into account when exploring innovation decisions.

**Limitations and Conclusion**

We acknowledge some important limitations, which also indicate directions for future research. First, in line with previous upper echelons studies, reverse causality and endogeneity may be potential concerns. It is plausible that a firm requiring application innovation hires a CEO with more diverse work experience; or a firm intending product innovation selects a CEO with more industry related experience to fulfill that task. Analysis of data with some instrumental variables may help address this concern. Second, while we focus on CEO only as the decision maker, it is likely that other members of the top management team are important decision makers. Future research should expand beyond the CEO. As Bourgeois (1980) and Hambrick (1981) suggest, “Although it is true that in most firms the chief executives has the most power, it still is of interest to study management teams”. Third, our data limitations did not allow the use of control variables for other CEO characteristics such as educational and functional background, and we are currently collecting data on those and several other relevant control variables.

In conclusion, this paper shows that a firm’s technological capability and CEO experience independently and jointly influence the firm’s innovation choices during the time of industry emergence. Our findings suggest that examining the role of capability without taking
into account the role of cognition offers only an incomplete explanation. The independent effect of technological capability does not hold when interaction terms are added to the model. In addition, the independent effects of CEO experience (especially experience diversity) persist even after adding the interaction terms. This further highlights the important role of cognition in explaining firms’ choices. Future research could uncover the underlying cognitive and psychological processes that make different CEOs deploy the same set of resources in different ways. Lastly, we only tested the hypotheses of this study using data from a single industry. Future research could examine whether the same product versus application innovation distinction applies in other emerging industries, and further test if technological capability and CEO background have similar effects in other industry settings. We believe that this paper provides novel insights about innovation choices and how a firm’s capability and cognition independently and jointly influence such choices during the time of industry emergence.
3.7 REFERENCES


### Table 3-1 Examples of Small Satellite Product and Application Innovations

<table>
<thead>
<tr>
<th>Examples of Small Satellite Product Innovation</th>
<th>Examples of Small Satellite Application Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Satellites: ArduSat1 and ArduSatX that utilized Audrino boards as the core of the avionics system (Developed by Spire)</td>
<td>- Communication: High-speed internet connection using small satellite constellations (developed by OneWeb)</td>
</tr>
<tr>
<td>- Ground equipment systems: New ground equipment control system for smallsats utilizing the “controller area network bus protocol” (Developed by Surrey Space Technology)</td>
<td>- Meteorology: Weather analysis software that that satellite data to monitor climate change (developed by Planalytics)</td>
</tr>
<tr>
<td>- Satellite control system: Highly automated command and control (C2) software such as quantumCMD used in cubesats (Developed by Kratos)</td>
<td>- Biology: New protein component developed under micro gravity using small satellites (developed by Emerald Bio)</td>
</tr>
</tbody>
</table>

### Table 3-2 Top Ten Patent Classes in the Satellite Industry

<table>
<thead>
<tr>
<th>Patent Class</th>
<th># of patents</th>
<th>%</th>
<th>Cumulative %</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B64G</td>
<td>253</td>
<td>14.16</td>
<td>14.16</td>
<td>Cosmonautics; vehicles or equipment therefor</td>
</tr>
<tr>
<td>H01Q</td>
<td>224</td>
<td>12.53</td>
<td>26.69</td>
<td>Aerials (routers or aerials for microwave heating)</td>
</tr>
<tr>
<td>H04B</td>
<td>148</td>
<td>8.28</td>
<td>34.97</td>
<td>Transmission</td>
</tr>
<tr>
<td>G01S</td>
<td>86</td>
<td>4.81</td>
<td>39.79</td>
<td>Radio direction-finding; radio navigation; determining distance or velocity by use of radio waves;</td>
</tr>
<tr>
<td>F02K</td>
<td>59</td>
<td>3.3</td>
<td>43.09</td>
<td>Jet-propulsion plants</td>
</tr>
<tr>
<td>H01P</td>
<td>55</td>
<td>3.08</td>
<td>46.17</td>
<td>Waveguides; resonators, lines or other devices of the waveguide type</td>
</tr>
<tr>
<td>H01M</td>
<td>35</td>
<td>1.96</td>
<td>48.13</td>
<td>Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy</td>
</tr>
<tr>
<td>G05D</td>
<td>34</td>
<td>1.9</td>
<td>50.03</td>
<td>Systems for controlling or regulating non-electric variables</td>
</tr>
<tr>
<td>F01D</td>
<td>24</td>
<td>1.34</td>
<td>51.37</td>
<td>Non-positive-displacement machines or engines, e.g. steam turbines</td>
</tr>
<tr>
<td>H04L</td>
<td>24</td>
<td>1.34</td>
<td>52.71</td>
<td>Transmission of digital information, e.g. telegraphic communication</td>
</tr>
<tr>
<td>Variable</td>
<td>Definition</td>
<td>Mean</td>
<td>SD</td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>1 Product</td>
<td>Equals 1 if the firm has introduced a new product or services that focuses on small satellite components, system integration, ground equipment, control system, or launch system, 0 otherwise</td>
<td>0.54</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>2 Application</td>
<td>Equals 1 if the firm has introduced a new product or services that apply small satellite technology to other areas such as internet service, earth observation etc., 0 otherwise</td>
<td>0.47</td>
<td>0.5</td>
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</tr>
<tr>
<td>3 Tech Related</td>
<td>The overlap of a focal company’s patent with those of emerging technologies in terms of patent classes</td>
<td>0.16</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>4 Tech Diverse</td>
<td>A Herfindahl index calculated using the share and number of patents in each patent class</td>
<td>0.6</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>5 CEO Related</td>
<td>The number of years the CEO of the firm has worked in space and aviation industry divided by the total number of years this CEO has ever worked</td>
<td>0.82</td>
<td>1.03</td>
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<tr>
<td>6 CEO Diverse</td>
<td>The number of different industries the CEO has worked in prior to joining the firm</td>
<td>2.63</td>
<td>1.81</td>
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</tr>
<tr>
<td>7 Firm Age</td>
<td>The age of the firm in years</td>
<td>22.07</td>
<td>20.55</td>
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<tr>
<td>8 NSG Rank</td>
<td>The ranking of the firm in the New Space Global Database</td>
<td>273.19</td>
<td>188.87</td>
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<tr>
<td>9 Avg Emp</td>
<td>Estimated average number of firm employees from the New Space Global Database</td>
<td>474.55</td>
<td>1421.8</td>
<td></td>
</tr>
<tr>
<td>10 NorthAmer</td>
<td>Equals 1 if the firm is headquartered in North America</td>
<td>0.71</td>
<td>0.45</td>
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</tr>
<tr>
<td>11 Asia</td>
<td>Equals 1 if the firm is headquartered in Asia</td>
<td>0.06</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>12 NSG MGT</td>
<td>New Space Global’s rating of the firm’s management team</td>
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<tr>
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Table 3-4 Correlation Matrix

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<td>0.01</td>
<td>0.11</td>
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<td>-<strong>0.89</strong></td>
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<td><strong>0.15</strong></td>
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<td>0.12</td>
<td>0.05</td>
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</table>

n=196; Correlation significant at 5% are shown in bold
### Table 3-5 Logit Regression Results

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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<tbody>
<tr>
<td><strong>H1a: Tech Relatedness</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product</td>
<td>3.408**</td>
<td>-3.357**</td>
<td>2.105*</td>
<td>-2.762**</td>
<td>0.490</td>
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<tr>
<td></td>
<td>(1.172)</td>
<td>(1.178)</td>
<td>(1.272)</td>
<td>(1.346)</td>
<td>(2.239)</td>
<td>(2.237)</td>
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<tr>
<td><strong>H1b: Tech Diversity</strong></td>
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<td></td>
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<tr>
<td>Product</td>
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<td>(0.736)</td>
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</tr>
<tr>
<td>Product</td>
<td>1.259***</td>
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<td>0.937***</td>
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<td></td>
<td>(0.307)</td>
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<td>(0.300)</td>
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<td><strong>H3a: Tech Related * CEO Diverse</strong></td>
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<td>(0.004)</td>
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<tr>
<td><strong>NSG Rank</strong></td>
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<td>(0.379)</td>
<td>(0.388)</td>
<td>(0.399)</td>
<td>(0.446)</td>
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<tr>
<td><strong>Average employees</strong></td>
<td>0.238</td>
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<td>0.463</td>
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<td>(0.233)</td>
<td>(0.233)</td>
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<td><strong>Market NSG score</strong></td>
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<td>0.469*</td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
<td>(0.223)</td>
<td>(0.223)</td>
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<td>(0.256)</td>
<td>(0.266)</td>
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<td><strong>Captchaization NSG</strong></td>
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<td>-0.002</td>
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<td>-0.000</td>
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</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.008)</td>
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<tr>
<td><strong>Technology NSG score</strong></td>
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<td>4.008</td>
<td>-8.930</td>
<td>6.186</td>
<td>-5.582</td>
</tr>
<tr>
<td><strong>Average Revenue</strong></td>
<td>25.49</td>
<td>34.58</td>
<td>33.53</td>
<td>59.46</td>
<td>76.57</td>
<td>78.26</td>
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<tr>
<td><strong>Constant</strong></td>
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<td>196</td>
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<td>34.58</td>
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<td>59.46</td>
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<td>78.26</td>
</tr>
<tr>
<td><strong>Pseudo R square</strong></td>
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<td>0.1251</td>
<td>0.2218</td>
<td>0.2944</td>
<td>0.3009</td>
</tr>
</tbody>
</table>

* p<0.1 **p<0.05 ***p<0.01
Figure 3-1 Conceptual Model of Paper Two

**Technological capabilities**
- Technological resource diversity
- Technological resource relatedness

**CEO experience**
- Diversity of industry experience
- Relatedness of industry experience

**Resource/knowledge based explanations:**
Choice is made based on optimizing resource deployment:
amplify resource strength, suffocate resource weakness

**Innovation choices**
- Creation of new products
- Creation of new applications

**Interactive effect:**
CEO background filter and distort his/her perception of the firm's technological capabilities

H1a, H1b

H3a, H3b

H2a, H2b

Upper echelons based explanations:
Choice is a reflection of the decision maker’s cognitive base and values

108
First Cubesat Opal and Picosats were successfully launched.

1999
Introduction of Cubesats, which set an industry standard for smallsats.

1987
Inception of the Utah State SmallSat conference and the “Meeting the Lightweight Satellite Systems” conference.

Limited capacity of launch vehicles limits the size of satellites.
Growing launch vehicle capacity enables heavier and more capable payloads.
Technological advancements in key satellite components including microprocessors, solar cells, batteries etc.
Modular systems and commercial off the shelf components made satellites smaller, faster and cheaper.
Growing private sector investment in satellite technologies and increased commercial use of satellites.

2000
Smallsats with greater capabilities were launched.

2000s
The number of small satellite launched exceeded the number of typical large satellite launched.

Key events related to small satellites:

Early 1990s
Establishment of large commercial communication smallsat constellations such as Iridium and Orbcomm.

1981
First modern microsatellite UoSat-1 successfully launched.

1970s to early 1980s
“Small satellite doldrums”

1957
First small and artificial earth satellite Sputnik 1 launched.

Early 1960s
Surge in launches of smallsats.

1987
First Cubesat Opal and Picosats were successfully launched.

Key trends of the satellite industry:
Figure 3-3 The Moderating Effect of CEO Experience Diversity on the Relationship between Technology Relatedness and Product Innovation

- CEO has worked in 1 industry
- CEO has worked in 5 different industries

Figure 3-4 The Moderating Effect of CEO Experience Relatedness on the Relationship between Technology Diversity and Application Innovation

- CEO has worked in the space industry for 0 years
- CEO has worked in the space industry for 10 years

Note: Figures are created using standardized regression coefficients
CHAPTER 4 : PAPER THREE

HOW DOES THE INNOVATION ECOSYSTEM INFLUENCE INDUSTRY EVOLUTION? EVIDENCE FROM THE SATELLITE INDUSTRY

4.1 INTRODUCTION

Industry life cycle models have identified several regularities in the aging pattern of an industry (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Jovanovic & MacDonald, 1994; Klepper, 1997). Since technological competition is often viewed as the primary driver of industry evolution (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Gort & Klepper, 1982; Utterback, 1994), and technological evolution and industry evolution are “inextricably linked” (Agarwal and Tripsas, 2008: 3), scholars have mostly focused on the roles of technology producers and customers in explaining the industry life cycle patterns. One of the regularities is observed during the emergence stage when levels of uncertainties for technology producers and customers are very high. Even though there are more product innovations, the initial sales levels are low. With the emergence of a dominant design, the industry progresses to the growth stage. Establishment of a dominant design allows firms to have standardized productions and to shift their focus to process innovation. Sales also dramatically increase after a dominant design emerges in the growth stage. As the return on investment in technology falls, the level of innovation decreases, the technology reaches its performance limits, and the industry moves to the mature and decline stages.

While many empirical studies offer findings that support the model’s key assertions (Argyres & Bigelow, 2007; Rothaermel, 2000; Tan & Mathews, 2010), other studies have challenged them (Klepper & Thompson, 2006; Krafft, 2004; Swaminathan, 1998). For example, McGahan and Silverman (2001)’s study of eight different industries including agriculture,
mining, manufacturing, and transportation found no evidence to clearly support the above mentioned patterns. The level of patenting activity does not decrease as the industries matured, and there is no evidence of a shift from product to process innovation. Similarly, Henderson (1995) has found that the existing industry life cycle theory could not fully explain the unexpected long age of the optical lithography industry. In addition, in my examination of the satellite industry, I did not find an immediate sales increase after the emergence of a dominant design. While the dominant design of small satellites CubeSat was first introduced in 1999, the dramatic sales increase did not start until early 2010, and it took more than ten years for small satellites to become the dominant technology in the market.

I argue that these observed irregularities occur for two different reasons. First, only focusing on the role of technology producers and customers offers incomplete explanations to the evolution of an industry (Adner & Kapoor, 2016; Stieglitz & Heine, 2007). The critical roles of other actors in the innovation ecosystem, such as the influences from component providers and complementors, have been largely ignored. However, the evolution of an industry is not only driven by changes in technological performance and customer demands, but also by more systematic efforts from the product component suppliers to complement service providers (Adner & Kapoor, 2010, 2016). For example, electric vehicles have demonstrated their superior cost performance with lower fuel cost per mile compared to traditional gasoline-fueled vehicles. The market also shows accelerated demand in cars using more environmentally friendly energy sources. However, technological challenges in lithium batteries (a key component of electric cars) and the lack of infrastructure such as charging stations (a key complementary service) have limited the market growth of electric cars. Therefore, in this paper, I take a more structural approach and ask: How does the innovation ecosystem influence industry evolution?
Second, the life of an industry often does not end with its maturity or decline. A subsequent technological discontinuity often happens in the later stages of an industry, and it creates a second wave of turbulence very similar to the first stage of the industry life cycle (Agarwal & Tripsas, 2008). Existing studies in technological discontinuities also show that there are multiple cycles of disruptive and incremental changes within an industry (Henderson, 1993; Tripsas, 1997). Yet, we know very little about how the subsequent life cycle differs from the previous one, and how the roles of the different actors in the innovation ecosystem change from the first to the second cycle. Therefore, in this paper, I also explore this question: How does the role of the innovation ecosystem change from one industry lifecycle to another?

To answer the above-mentioned research questions, in this paper, I build on the industry evolution (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Gort & Klepper, 1982; Jovanovic & MacDonald, 1994; Klepper, 1996; Utterback, 1994) and the innovation ecosystem (Adner & Kapoor, 2010, 2016; Ethiraj, 2007; Henderson, 1995; Woolley, 2014) literature and examine the evolution of the satellite industry. I use both qualitative and quantitative research methods and examine the evolution of this industry from 1957 (the year when the first satellite was launched) to 2015. I found that the satellite industry is transitioning from its first life cycle to its second life cycle. The first industry cycle (from 1957 to 1981) generally follows the key patterns of the industry evolution model. In 1981, the first modern small satellite was successfully launched. The modern small satellite technology significantly increased the performance per price ratio of satellites, and it has caused technology discontinuities that disrupted the existing satellite industry and created a new period of turbulence. However, the newly emerging (small) satellite industry has shown many irregularities. The technology was successfully demonstrated in 1981, and a dominant design emerged in 1999, but new firm entry
levels and sales levels did not start to increase until early 2010, and the small satellite technology did not become dominant until 2012.

To explain these irregularities, I identify satellite component providers such as battery suppliers, complementors such as launch vehicle providers, and customers such as satellite operators as important actors in the innovation ecosystem (Adner & Kapoor, 2010, 2016). Time series analysis of the small satellite market share during the past 58 years shows that the availability of launch vehicles and changing customer demand had a critical impact on the evolution of the satellite industry. Their effects are even stronger compared to the manufacture of the satellites themselves.

The importance of each actor in the innovation ecosystem also changes in the two different industry life cycles. I found that during the beginning of the satellite industry, availability of complementary technology greatly determined the use of small versus large satellites. As the industry evolved, technologies with greater performance (regardless of their price) became increasingly attractive. During the growth stage, performance of the focal technology was the key factor that influenced industry evolution. Small satellite technologies became dominant in early 2010 with the increased interest in finding novel applications of small satellites. During this second industry lifecycle, the changing customer demands became the most critical reason that caused the surge in small satellite launches.

The rest of this paper proceeds as follows: I first review literature on industry evolution and the innovation ecosystem to provide a theoretical foundation for my empirical analyses. Next, I describe the satellite industry as my research context and explain my data sources and analytical methods. I then answer the research questions through in-depth case analyses and time
series regression analysis using data from the satellite industry. Lastly, I discuss results, integrate findings from each analysis, and provide implications for future research.

4.2 LITERATURE ON INDUSTRY EVOLUTION AND THE INNOVATION ECOSYSTEM

Stages of Industry Life Cycle

Industry lifecycle literature proposes several models to characterize the different phases of an industry. At the broader industry level, scholars have identified industry phases such as emergence, growth, maturity, and decline (Auster, 1992; Covin & Slevin, 1990; Low & Abrahamson, 1997; Porter, 1980). At the product unit level, Abernathy and Utterback (1978) proposed three stages from fluid, transitional, to specific. At the technology level, scholars have mostly focused on the cycles of technological discontinuities and separated the ferment stage from the incremental change stage (Anderson & Tushman, 1990). Although each literature stream disagrees somewhat on the specific evolutionary stages, the different phases of industry evolution are commonly characterized by variations in technological designs, levels of uncertainties to producers and customers, and competitive emphasis (Abernathy & Clark, 1985; Abernathy & Utterback, 1978; Klepper, 1997; Peltoniemi, 2011; Utterback, 1994). Since the level of analysis of this paper is the industry level, I follow previous literature (Covin & Slevin, 1990; Low & Abrahamson, 1997) and adopt the most frequently used emergence, growth (or shakeout), and mature to capture the three stages of the industry lifecycle. Table 4-1 provides a summary of the key characteristics of each industry life cycle stage.

[Insert Table 4-1 about here]

Industry life cycle theorists posit that industry emergence is often a product of technological discontinuities (Anderson & Tushman, 1990; Klepper, 1997). Technological
discontinuities include “a change in the competence needed to produce the product, a change in the physical product or its production process, or a sharp increase in the performance per price ratio” (Peltoniemi et al, 2011: 350).

The first stage of industry evolution, the emergence stage, is often characterized by high levels of uncertainties for producers and customers, frequent technological changes, and various product designs (Abernathy & Utterback, 1978; Agarwal & Sarkar, 2002). During industry emergence, neither the producers nor the customers are certain about what the new technology can do, what the most important features are, or what the key challenges and obstacles in designing and using the technology would be (Cusumano, Kahl & Suarez, 2015). For example, when personal computers were first introduced, most users were unclear about what computers could do and how they would be used. On the producers’ side, without established technological paradigms and technological trajectories, firms in the emerging stage were still experimenting with different technology alternatives, and the failure rate was often high (Abernathy & Utterback, 1978; Clark, 1985; Dosi, 1982; Kazanjian, 1988). As a result, product variation was high, but the output level was relatively low during the emerging phase (Cusumano et al., 2015).

As various technological designs began to converge to a dominant design, the industry evolution shifts from emergence to the second stage – growth (or shakeout). The end of the era of early exploration is often marked by the emergence of dominant designs. A dominant design is “a single architecture that establishes dominance in a product class” (Anderson and Tushman, 1990: 613). The emergence of dominant designs is a key event of technological evolution as it marks the product innovation transition from a fluid to a specific pattern (Abernathy and Utterback, 1978). Following the emergence of dominant designs, subsequent technological advancements often focus on incremental improvements of the standards (Abernathy and
Utterback, 1978). As shown by Tschang (2007), in the video game industry, with the emergence of established product designs, both customers and producers desire incremental innovative games. During this stage, video game publishers often focused on making game sequels. Another example is that in the cell phone industry, Apple’s iPhone has been one of the established standards of the smart phone product class. Since the introduction of the first iPhone, Apple has focused most of its efforts on improving the iPhone model and introducing upgrades such as iPhone 3-7 as incremental improvements of the dominant design.

Other than the emergence of dominant designs, the growth stage of the industry life cycle is also characterized by reduced uncertainties for producers and customers and growing market demand around these standardized products (Cusumano et al., 2015). For producers, the emergence of dominant designs permits firms to have a stable large volume of production. The predominant type of innovation changes from product innovation to process innovation that improves efficiencies (Abernathy and Utterback, 1978). The competitive focus shifts to process innovation instead of product innovation. Firms that are unable to improve their efficiencies are less likely to survive because of increased competition (Klepper, 1996). During the growth stage, there is often a shakeout in the number of producers. The number of producers declines despite the continued growth in industry output. For consumers, having standards also reduces the confusion about various product designs and performance. Market definition is sharpened. Decreased uncertainty increases market demand and production volume.

As the industry shifts from growth to the last stage of maturity, the levels of uncertainties dramatically decrease for both producers and consumers. The technology becomes more standardized and undifferentiated, and competition emphasis shifts to cost reduction (Abernathy & Utterback, 1978; Auster, 1992). As a result, technologies are more like commodities. During
the mature stage of industry evolution, innovation is mainly stimulated by pressure to reduce cost and improve quality (Abernathy & Utterback, 1978). The form of innovation changes from a fluid pattern to a specific pattern (Abernathy and Utterback, 1978). The mature stage is also accompanied by “heightened price competition and increased emphasis on process innovation. Small-scale units that are flexible and highly reliant on manual labor and craft skills utilizing general purpose equipment develop into units that rely on automated, equipment-intensive, high-volume processes” (Abernathy and Utterback, 1978:6). Technological innovation in the mature stage may have equal or greater commercial importance compared to the first two stages previously discussed.

It is important to note that the mature stage does not mark the end of the industry lifecycle. Existing studies in technological discontinuities show that there are often multiple cycles of disruptive and incremental changes within an industry (Agarwal & Tripsas, 2008; Anderson & Tushman, 1990). Much of the subsequent technological discontinuity happens in the mature stage of the industry, and it creates a second wave of turbulence very similar to the first stage of the industry life cycle (Agarwal & Tripsas, 2008). Research has shown how subsequent technological discontinuities have started new industry life cycles in the photolithography (Henderson, 1993) and typesetter (Tripsas, 1997) industries. Yet, few papers have compared the differences between two life cycles in the same industries, and we know very little about whether the two life cycles will follow the same patterns and share the same drivers.

**Actors in the Innovation Ecosystem**

Even though most of the literature has explained industry evolution using performance of the focal technology and customer demand, innovation ecosystem literature (Adner & Kapoor,
2016; Ethiraj, 2007; Henderson, 1995) has started to point out that the technology substitution is not between the new and old technology; it is between the two innovation ecosystems.

Innovation ecosystems – “the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution” (Adner, 2006: 98) highlights the interdependencies among different actors in the system. The ecosystem perspective suggests that the evolution of an industry and the successful adoption of a new technology depend not only on the performance of the technology itself, but also on the evolution of other industries and adoption of other innovations in the ecosystem (Adner & Kapoor, 2010). Without the supporting infrastructure, a technology cannot realize its full potential to its customers (Adner, 2006). For example, while Airbus is the core innovator of the pioneering aircraft A380, its manufacturing is highly dependent on component suppliers providing engines, complementors such as the airports developing new infrastructures to accommodate the size, regulators implementing new safety procedures, and customers such as airlines providing trainings to their pilots to operate the new aircraft. Thus, the successful adoption of the A380 aircraft is a result of collaborative efforts from different actors in the innovation ecosystem. Similarly, in Woolley (2014)’s examination of emerging nanotechnology, she has also found that government agencies, universities, national laboratories, new and incumbent firms jointly supported the development of nanotechnology. She noted that “the elements of infrastructure supporting nanotechnology entrepreneurship were not created in isolation; rather they required the development of each other” (Woolley, 2014: 737). She further referred to this collaborative endeavor as “systematic coevolution”. In this paper, I follow the approach used by Adner and Kapoor (2010, 2016) and focus on examining the role of complementors, component suppliers, and customers in the innovation ecosystem.
The upstream suppliers provide the necessary components focal firms need to integrate for their customers. Without all the necessary components, the focal firm cannot offer a complete product to its customers. The complementors, on the other hand, do not inhibit the focal firm from offering its product to customers. However, without the necessary complementary technology, customers cannot fully utilize the product’s potential (Adner & Kapoor, 2016; Stieglitz & Heine, 2007). For example, computer software is the complementary product of computer hardware. Without any software, consumers can still purchase computer hardware, but they cannot fully utilize the functionality of a computer.

Scholars have already started to emphasize how advances in the performance of component technologies and significant changes in the needs and capability of users could influence industry evolution. For example, Henderson (1995:641) examined the optical lithography industry and concluded that “the belief that the limits of a technology are determined by the internal structure of the technology may be fundamentally misleading”. The unexpected long life of the optical lithography industry suggested that technical limits are highly influenced by advances in component and complementary technologies, and the capabilities of users. Adner and Kapoor (2016: 628) also argued that “the performance that matters to the consumers’ assessment of value – the realized performance – is not the performance of the focal technology on its own, but is rather a function of its interaction with the other elements of the system.”

Studying industry evolution from the entire ecosystem is important because of technological interdependencies – the realized performance of a technology can be hindered by technical bottlenecks within the system. “Only after the emergence challenges of these complements were resolved that the new generations of tools could finally deliver performance
that matched their potential, and market adoption could begin in earnest” (Adner and Kapoor, 2016: 628).

4.3 IRREGULARITIES IN THE EVOLUTION OF THE SATELLITE INDUSTRY

Data Sources

I use data from the satellite industry to examine the role of the innovation ecosystem in industry evolution. The satellite industry emerged in 1957, when the Soviet Union launched the first artificial satellite, Sputnik 1. I followed and tracked more than 7,000 satellites that have been successfully launched from 1957 to 2015. For each satellite, I collected data such as launch date, mass, launch vehicle, manufacturer, operator, and application purpose from Gunter’s Space Page. Missing values on satellite mass were gathered from NASA.gov, Encyclopedia Astronautica, and Spacecraft Encyclopedia. Additional information on the key events, trends, and explanations of technological substitution were gathered from the Small Satellite Conference proceedings, two books on small satellites: Small Satellites: Past, Present and Future by Helvajian and Janson (2008), and Small Satellites and Their Regulation by Jakhu and Pelton (2013). I also conducted interviews with more than ten industry experts to develop a basic understanding of the industry, to identify key technological trends and obstacles, and to confirm my explanations and results.

Life Cycles and Key Stages of the Satellite Industry

Using patterns and criteria described above in the industry life cycle literature (Abernathy & Utterback, 1978; Klepper, 1996, 1997), I identified several key stages of the evolution of the satellite industry. Table 4-2 summarizes the chronology of key events.

[Insert Table 4-2 about here]
First Industry Life Cycle: Emergence Stage (1957 to Mid 1960s). The emergence stage of the first satellite industry lifecycle starts in 1957 and ends in the mid-1960s. On October 4th, 1957, the Soviet Union successfully launched the world's first artificial satellite, Sputnik 1, which marked the beginning of the satellite industry. Figure 4-1 summaries the total number of satellite launches by year, Figure 4-2 shows the number of large and small satellites (defined later in this paper) launches by year, and Figure 4-3 depicts the number of new satellite manufacturer entries per year. Firm entry rate is one of the most important characteristics that has been used in previous literature to identify industry stages (McGahan & Silverman, 2001). As shown in Figure 4-3, there was a continuous growth in new firm entries until 1966. New firm entries reached an inflection point in 1966, and the entry rate started to decrease and progressed to a shakeout period after 1966.

First Industry Life Cycle: Growth/Shakeout Stage (Mid-1960s to 1981). The emergence of dominant designs marked the end of the emergence era and the beginning of the growth stage. Table 4-3 summarizes the most frequently used satellite designs. It is important to note that the dominant designs of satellites started to emerge around the mid-1960s, which signaled the industry’s evolution to the growth or shakeout stage. During this period, four satellite designs, namely, Kosmos (Zenit-2), KH-4A (Corona, OPS), Kosmos 36 (DS-P1-Yu), and Molniya, were introduced, and more than 370 satellites that were successfully launched used similar designs. During the growth stage, as shown in Figure 4-1, the number of satellites that were successfully launched significantly increased compared to the emergence stage.
Second Industry Life Cycle: Continued Growth and Shakeout (1981 to early 2010s). In 1981, using available commercial off-the-shelf (COTS) components, the first modern microsatellite, UoSat-1, was successfully developed by Sir Martin Sweeting from the University of Surrey. According to SpaceWorks’ (a satellite industry consulting firm) Nano/Microsatellite Market Assessment Report, large satellites refer to artificial satellites with a wet mass of more than 500kg, and small satellites refer to artificial satellites with a wet mass under 500kg. The UoSat-1 first demonstrated that relatively small and inexpensive satellites could be built rapidly to perform successful and sophisticated missions. Modern small satellite technology has caused technology discontinuities in the satellite industry and started a new industry lifecycle. Yet, there was no dramatic increase in the total number of satellites launched or the number of new firm entries during this time frame, and the industry experienced continued shakeout during this period.

Second Industry Life Cycle: New Emergence (early 2010s to present): As shown in Figure 4-2, modern small satellite technology did not become widely used until the early 2010s. Since then, there has been a surge in the total number of satellites successfully launched, and there has been a dramatic increase in the number of entries of new satellite manufacturers. The wide use if modern small satellite technology shows that consumers have shifted their interest from large satellites with advanced capabilities to smaller satellites that offer more competitive prices.

Irregularities in the Satellite Industry Life Cycle

Even though the key events described above are helpful in identifying the different stages of the satellite industry life cycle, the evolution of the satellite industry did not follow many patterns that have been observed in previous literature.
First, while the successful launch of the first modern small satellite in 1981 signaled the emergence of a new industry life cycle, the number of new firm entries did not increase in the 1980s. The industry life cycle model posits that the emergence of an industry is often a product of new technological opportunities caused by technological discontinuities (Peltoniemi, 2011). Technological discontinuities range from a change in the competence needed to produce a product, or a sharp increase in the performance per price ratio (Peltoniemi, 2011). During the early years of the satellite industry, the successful launch of Sputnik-1 demonstrated how orbiting spacecraft could survive in the hostile environment of space. In the second industry lifecycle, the successful launch of the first modern small satellite caused another type of technological discontinuity that sharply increased the performance per price ratio of satellites. Yet, unlike patterns that have been identified in industry evolution literature, there were no high levels of firm entries after the successful demonstration of this technological discontinuity.

Second, the number of small satellite launches did not increase right after the introduction of small satellite dominant designs – the CubeSats. In 1999, Professor Jordi Puig-Suari of California Polytechnic State University and Professor Bob Twiggs of Stanford University first developed the CubeSat to give universities more opportunities to use satellite technologies for space-related scientific research. CubeSats are made up of multiples of 10×10×10 cm cubic units, and a basic CubeSat unit has a maximum mass of 1.33 kg. The standardized CubeSat design reduces the cost of deployment and gives small satellites more opportunities to be launched as secondary payloads; it significantly minimizes risk to the rest of the launch vehicles and payloads. CubeSat’s small size and light weight significantly reduced the launch cost to around $40,000 per launch, while the mean launch cost for a typical large satellite is around 100 to 400 million dollars. The invention of CubeSats offers a fast and affordable way for a wide
range of interested stakeholders to be active in space and allows for a fast innovation cycle. Since its first introduction, CubeSats have become the standard configuration of small satellites, and they have been used in a large number of satellite configurations. For example, all 127 Flock satellites designed by Planet Labs have used the CubeSat configuration. The industry evolution model predicts that the output level will increase significantly after the introduction of new dominant designs. Yet, for the ten years after the introduction of CubeSats, the number of small satellite launches was not higher compared to previous time periods. The use of CubeSats was still mostly limited to universities, and customers were still unclear about what small satellites could do.

Lastly, before the introduction of the modern small satellite technology and the CubeSats standard, large satellites had a clear performance advantage compared to traditional small satellites. Large satellites allowed higher payload capability and offered more advanced capabilities. Yet, in the beginning of the satellite history, small satellites had higher market share compared to large satellites. The high market share of small satellites cannot be explained by the performance advantage of large satellites.

4.4 THE ROLE OF INNOVATION ECOSYSTEM

Actors in the Satellite Industry Innovation Ecosystem

To explain these irregularities observed in the satellite industry, I examine the role of different actors in the satellite industry innovation ecosystem. Key actors in the innovation ecosystem include: satellite manufacturers, component suppliers, complementary service providers, and customers.

The design and manufacture of small satellites can be broken down into two parts. First is the spacecraft bus, which is “the platform that allows the spacecraft to support a particular
function in space” (Jakhu et al, 2013). The bus includes the power system, thermal control, ground surveillance and communication, stabilization and pointing systems, tracking, telemetry, and command and monitoring that support the mission. The second part is the payload, which is “the hardware that is specifically designed to carry out the mission” (such as communication, navigation, earth observation, etc.) (Jakhu & Pelton, 2013). The payload defines the satellite’s essence and mission. Small and large satellite manufacturers use payload and spacecraft bus components to build satellites, which are defined as the focal technologies in this paper. In order to realize the value of satellites, complementary services such as satellite launches and ground communications are needed. Finally, large or small satellite manufacturers could deliver their products to customers – the satellite operators. Satellite operators then use the satellites for different application purposes such as communication, earth observation, navigation, manned spacecraft, and reconnaissance. Figure 4-4 illustrates the innovation ecosystem of the satellite industry.

[Insert Figure 4-4 about here]

Interdependencies Among Different Actors

During conference interviews, several industry experts underscored the interdependent and collaborative nature of the small satellite industry. For example, the Small Satellite Conference organized by the Utah State University is one of biggest conferences in the small satellite community, and this conference was first started in 1986 to bring the community together after the Challenger shuttle blew up. One of the industry experts commented: “In Spring of ‘86, they (employees at Utah State University) said we should have a conference and get everybody that’s doing something together and really building things and having businesses built on these things, we should get them together and strategize on how we’re going to survive.
That’s why this conference started. From then on, this conference has always been about people actually doing real work and sharing”. Another industry expert commented on the value chain in the satellite industry and different actors in the innovation ecosystem: “The whole stream of companies…someone who builds the camera, someone who builds the satellite, someone who builds the rocket, someone who puts it on the rocket, and then that goes into space, someone who builds the ground stations that that satellite communicates with to the satellite up in space, and that gets JPEG pictures back to another company, who sells those pictures to another company and then that company processes it.” These conference interviews have highlighted the collaborative nature of this industry and helped me to better understand the key actors in the ecosystem. Figure 4-5 illustrates the key events in the innovation ecosystem, and how these events have influenced changes in the small satellite market share.

[Insert Figure 4-5 about here]

The interdependencies among different actors in the innovation ecosystem are also demonstrated in the following ways. First, the success of a focal product is dependent on the success of other products in the innovation ecosystem (Adner & Kapoor, 2010). Consider the innovation ecosystem of the AMOS 6 satellite (illustrated in Figure 4-6) – MacDonald, Dettwiler and Associates; Thales Alenia Space; and other suppliers provided the electric propulsion system, the communication payload, and other components to the satellite manufacturer. The Israel Aerospace Industries integrated these components together and built the AMOS 6 satellite. SpaceX scheduled to launch the satellite on the Falcon 9 rocket, and Spacecom planned to be the main operator of this satellite. Facebook and EutelSat signed a $95 million contract to lease the Ka-band capacity from Spacecom. They planned to utilize the band capacity to provide Internet services in rural regions. Two days prior to the satellite launch, the Falcon 9 rocket exploded
during a static fire test, and the AMOS 6 was destroyed. The satellite components were compromised in the explosion. Additionally, the satellite manufacturer had to file a claim with SpaceX to compensate the operator Spacecom. Lastly, Facebook was forced to delay its Internet service plan. Technological problems from the complementor have caused damage for almost every other actor in the innovation ecosystem. The success of the focal product – the AMOS 6 satellite – is dependent on the success of all the other products and services in the innovation ecosystem.

[Insert Figure 4-6 and 4-7 about here]

Second, each actor in the innovation ecosystem may play multiple roles, thus increasing the interdependencies among different actors. In the AMOS 6 example (illustrated in Figure 4-6), Thales Alenia Space played the role of a component supplier by providing the electric propulsion system to the focal producer – the Israel Aerospace Industries. Yet, in the innovation ecosystem of the O3b satellite (illustrated in Figure 4-7), Thales Alenia Space played the role of the focal technology producer. Thales Alenia Space integrated components provided from Moog Space and Defense Group and other component suppliers and built the O3b satellite. Thales delivered the satellite to its customer – O3b Networks – and O3b Network operated the satellite to provide Internet services. In a traditional industry setting, where each actor in the innovation ecosystem produces a different and market-specific product, the relationship between Thales Alenia Space and Israel Aerospace Industries can be exclusively competitive. That is, as established satellite manufacturers, they compete for same contracting opportunities from satellite operators. Yet, with more vertical integrations (Balakrishnan & Wernerfelt, 1986) in the current industry setting, and companies like Thales Alenia Space expanding its operations to provide satellite components, their relationship becomes more interdependent – the Israel Aerospace Industries
depends on Thales providing components with the most cutting-edge technologies, and Thales depends on having the Israel Aerospace Industries as one of its customers. The same actor may play different roles in different settings, thus increasing the complexity and interconnectedness of relationships. Therefore, interdependency is not only caused by the inter-relationship among different actors, it is also caused by multiple roles of the same actor.

Lastly, independency becomes even more important as the innovation ecosystem expands to include more actors. Compared with the innovation ecosystem of the O3b satellite (Figure 4-7), the innovation ecosystem of the AMOS 6 satellite (Figure 4-6) included an additional second-tier customer: Facebook. Facebook, a traditionally defined Internet company, is planning to offer the same type of services as offered by O3b Networks, a traditionally defined satellite operator. As the satellite industry evolved, established players from other industries often entered into the industry as second- or even third-tier customers. While the existing innovation ecosystem literature often only considers first-tier actors (Adner & Kapoor, 2010, 2016), second-tier customers like Facebook had an even greater impact. Facebook’s plan to utilize satellite technologies to provide Internet services in rural areas has attracted a lot of media attention, thus incentivizing more investments for satellite manufacturers, satellite operators, and launch vehicle providers. As the innovation ecosystem expands to include more diversifying entrants with greater influences, interdependency is not only among first-tier actors; the range of its impact becomes even broader.

**Role of Complementors**

The high market share of small satellites in the 1960s was highly influenced by limited launch vehicle capacities and high launch failure rates in the beginning of the satellite industry. As argued by Helvajian and Jason (2008:1), the sizes of the satellites during the early years of
the satellite industry development “were heavily influenced by the predecessor sounding rocket and missile programs that had been conducted by the United States and the Soviet Union before, during, and after World War II”. In the industry’s early years, all satellites tended to be small due to limited launch capacities of early launch vehicles. For example, in 1957, when the Soviet Union developed the first satellite launch vehicle Sputnik 1, it only had a payload of 500kg. In 1958, the United States Juno 1 launch vehicle had a payload to low earth orbit of 11kg. The Vanguard rocket had a payload of 9kg. The limited capacities of launch vehicles inhibited the adoption of large satellites in the early years, which explains the popularity of small satellites. In addition, high launch failure rates also contributed to the high market share of small satellites in the 1960s. As shown in Figure 4-8, the launch failure rates for satellites were extremely high in the first decade of satellite history. In 1958, 20 out of the 28 attempts to launch satellites were unsuccessful. When launch failure rates were high, small satellites were preferred over large satellites as small satellites had lower costs and were relatively easy to build.

Even though limited capacities of launch vehicles and high launch failure rates favored the development of small satellite technology in the 1950s-'60s, these problems were quickly resolved. By the late 1960s, as shown in Figure 4-8, launch failure rates were relatively low, and launch vehicles with large payload capacities had been developed. Large satellites with superior performance quickly became the dominant market technology, and most launch opportunities favored large satellites. Even after modern small satellite technology was successfully demonstrated in 1981, it was still difficult for small satellites to find launch opportunities. As mentioned by one of the industry experts I interviewed: “The problem until recently has always been there were more ideas for the small satellites than they could ever find a launch for. Everybody was always trying to find a launch and especially one that was free, because no one
had any money. At least in this country, starting about 1985 or about that time, the problem in this country was no one could find a launch. There were very few.” Therefore, limited access to complementary service inhibited the growth of small satellites’ market share in the 1980s.

Figure 4-9 also shows how the availability of complementary launch vehicles greatly influenced the small satellite market share in the emergence stage. As shown in the figure, before 1965, the number of launch vehicles available for small satellites was greater than the number of launch vehicles for large satellites. While having more available launch opportunities explained the dominance of small satellite technologies in the emergence stage, it does not explain the increased market share of small satellites after 2012. As shown in the figure, since 1965, there have always been more launch vehicles available for large satellites. Yet, despite the limited number of launch vehicles available, small satellites still managed to regain their market dominance in 2012, which shows that complementary products and services played critical roles in the emergence stage of the industry, but they became less critical in the later stages of the industry.

[Insert Figure 4-8 and 4-9 about here]

Role of Focal Technology Producers

During the growth stage, while complementary products and customer demands are also important factors, the superior performance of large satellites was the key reason why large satellite technologies dominate the market during this stage. As the industry evolved, “larger launch vehicles with larger payload capacities were developed, and ever-larger spacecraft were designed to ride on those vehicles” (Helvajian and Jason, 2008:52). Large satellites usually offer superior performance and capabilities compared to small satellites. In general, the average lifetime of small satellites is three years, which is only one-third that of typical large satellites
If we look at the specific performance of earth observation satellites, large satellites could offer resolution of lower than 30 cm, yet small satellites are still barely capable of sub-meter resolution (Purl, Gomes, da Silva Curiel, Cutter, Sun & Sweeting, 2006). Since small communication satellites are often placed in low earth orbits, they are not permanently visible. This causes “a major decline in performance for providing typical telecommunication services (e.g., TV broadcasting, phones) where service continuity is essential” (Paulino et al., 2016: 48). As mentioned and confirmed by many industry experts, the superior performance of large satellites was the key driver of the growth in large satellite market share in the growth or shakeout stage.

Role of Customers

Change in customer demand is an important driver of technology competition and substitution in all stages of an industry. Nonetheless, I argue that customer demand has the greatest influence in the second life cycle of the satellite industry. As discussed earlier, even though in the early developmental stages of the satellite industry, customers preferred large satellites with superior performance and capabilities, the key technological bottleneck in launch vehicles inhibited large satellites from being the dominant technology despite greater customer demand. Therefore, even with higher customer demand, without the availability of complementary technologies, customer requirements could not be fully satisfied in the emerge stage.

However, as the industry evolved into the mature phase, with necessary complementary technologies well developed, the change in customer demand greatly influenced small satellite market share. As shown in Figure 4-2, the number of small satellites that have been successfully launched has greatly increased since 2012. This recent surge in small satellite launches is
explained by the recent increase in small satellite operators as shown in Figure 4-10. A large number of new satellite operators became interested in small satellite technologies and started to develop novel applications of small satellites. For example, O3b Network is a company that plans to launch a constellation of small satellites to provide Internet service to developing countries.

Satellite applications changed significantly as the industry matured. Before 1965, major satellite applications included reconnaissance, military communication, manned spacecraft, and meteorology uses. However, in recent years, satellite applications have shifted from government and military uses to commercial uses such as communication, earth observation, and navigation. As mentioned by one of the industry experts I interviewed – “a lot of these companies are now getting into remote sensing. They don’t call themselves remote sensing companies. They pitch themselves as analytics companies. They see their value as not the photo they took, the value is in the information you can derive from it.” Another industry expert has also commented on the high gross margin of satellite operators in recent years. “The thing is the value chain from like the camera to the spacecraft to the launch to the ground system to the JPEG pictures. (The profit margin for) launch is very low. (The profit margin for) ground station is lower. JPEG picture is better in value. The value is really in seeing this picture and processing it. ” The high profit margin has attracted more satellite operators to enter the industry in recent years, and the recent increase in small satellite operators and the shifts in satellite applications are key drivers of high market share of small satellites after the 2010s.

Supplementary Time Series Analysis
Statistical Method and Measures. To empirically test the role of each actor in the innovation ecosystem on industry evolution, I conducted a time series analysis on the market share of small satellites from 1957 to 2015. Since this time series data raises issues such as autocorrelation – high correlation between the same variable in different time periods – I used the ARIMA model for my analysis. The Dickey-Fuller test shows that small satellite market share is stationary over time, and the AC and PAC statistics show that a one-year lag in the dependent variable provides the best model fit. Therefore, I used an AR (1) model.

The dependent variable small satellite market share was measured as the number of small satellites successfully launched divided by the total number of satellites launched in a given year. To examine the role of complementors, I used three variables related to the availability of launch vehicles. First, I calculated the percentage of small satellite launch opportunities using the number of launch vehicles available for small satellites divided by the total number of launch vehicles in a given year. Second, I calculated the launch failure rate by dividing the number of failed launches by the total number of attempted launches. Third, since most of the small satellites are launched as secondary payloads, I also included the percentage of satellites that were launched as secondary payloads in a given year. To capture the technological development of the focal satellite technology, I calculated the ratio of the number of small satellite manufacturers to large satellite manufacturers in a given year. Lastly, to measure market demands, I divided the number of small satellite operators by the number of large satellite operators. On average, it takes around two years for a satellite to be manufactured and launched. Therefore, I used a two-year lag in all of the explanatory variables. Descriptive statistics and correlations among variables are shown in Table 4-4.

[Insert Table 4-4 about here]
Role of Satellite Manufacturers. Results of the time series analysis are shown in Table 4-5. Model 1 tests the effects of small satellite manufacturers on small satellite market share. As shown in the regression table, having more small satellite manufacturers in the past year will significantly increase the market share of small satellites in the following year ($\beta = 0.23, p < 0.10$). However, the effect of having more small satellite manufacturers becomes smaller and insignificant ($\beta = 0.184, p > 0.10$) after controlling for the effects of satellite complementors and satellite operators. These findings show that while having more small satellite manufacturers may help the development of small satellite technology and increase market share, without enough launch opportunities and market demands, small satellites cannot substitute for large satellites.

[Insert Table 4-5 about here]

Role of Satellite Complementors. Model 2 tests the role of satellite complementors. Regression results show that having more small satellite launch vehicles will significantly increase small satellite market share ($\beta = 0.402, p < 0.05$), and if the failure rate is higher in the previous year, then small satellites are more frequently used in the next year ($\beta = 0.372, p < 0.05$). In addition, if there are more piggyback opportunities for satellites in the previous year, then the small satellite market share is more likely to increase in the next year ($\beta = 0.32, p < 0.05$). The results support my theoretical arguments: If more launch vehicles were available, or more opportunities to launch as secondary payloads were available for small satellites, then more small satellites could be launched into orbit. If the failure rates in previous years were high, then small satellites are also preferred over large satellites as the costs of building small satellites are much lower. It is important to note that while the effect of the number of launch vehicles becomes insignificant, the effects of the failure rate and piggyback opportunities persist in the
full model (model 4). Also, the effect sizes of all variables related to satellite complementors are greater than the effect sizes of satellite manufacturers, which further demonstrate the important role of satellite complementors.

Role of Satellite Operators. The role of satellite operators is tested in Model 3. Results in Model 3 show that having more small satellite operators in the previous two years does not increase the small satellite market share in the following year. However, in the full model (Model 4), after controlling for the effects of satellite manufacturers and complementors, I found that the increase in the percentage of small satellite operators in the previous two years could significantly increase the small satellite market share ($\beta = 0.194, p < 0.10$). Therefore, results show that having higher customer demand increases the likelihood of technology substitution of small satellites.

4.5 CONCLUSIONS AND DISCUSSION

The evolution of the satellite industry showed several irregularities that could not be explained by the existing industry evolution models (Abernathy & Utterback, 1978; Klepper, 1996, 1997). The superior performance of large satellites could not explain the high market share of small satellite technologies in the beginning of the satellite history. The successful technology demonstration of modern small satellite did not increase the number of new firm entries, and the establishment of the CubeSat dominant design was not quickly followed by increase in the output level of small satellites. Accordingly, this paper is motivated to explain these irregularities I observed in the satellite industry.

I argued that industry evolution cannot be fully explained by the performance of focal technologies, and I suggested the need to consider the role of complementors, customers, and technology producers. Influences of these actors in the innovation ecosystem help to explain
these irregularities. Table 4-6 illustrates how the innovation ecosystem perspective can provide novel explanations. In the beginning of the satellite industry, because launch vehicles had limited capacities and it was more challenging to launch large satellites, small satellites dominated the market. However, with the development of launch vehicle technologies and increases in launch vehicle capacities, large satellites were more frequently used in the 1970s and 80s. Small satellites were often launched as secondary payloads, and they cause additional risks for the primary payloads. Therefore, it was more difficult for small satellites to find launch opportunities. Limited launch opportunities have also stunted the growth of small satellite technologies in the 1980s. Lastly, technological advancements such as big data processing from satellite operators contributed to the recent surge in small satellite usage. I provided illustrative data and results supporting these arguments. The results show that transition from one industry stage to another requires collaborative efforts from the innovation ecosystem.

[Insert Table 4-6 about here]

**Value Creation in Innovation Ecosystem**

Results show that each actor in the innovation ecosystem provides unique yet interdependent values. Component suppliers provide *technological value* to focal technology producers. Innovations from focal technology producers are often caused by innovations from component suppliers (Abernathy & Utterback, 1978). Component suppliers provide technological ingredients that focal technology producers can utilize to improve the technological performance of their products. As shown by Adner and Kapoor (2010), technology leaders can better sustain their competitive advantage if their competitors face greater technological challenges in components. On the other hand, customers provide *market value* to focal technology producers. Customers define how the technology could be utilized and their
willingness to pay for performance improvement (Adner, 2002). Customers not only consider the performance of focal technologies, they also incorporate price into their decision making process, thus providing market value to focal technology producers. In the AMOS 6 satellite example, the high contracting fee Facebook paid to lease the Ka-Band capacity sets a market value of the satellite, thus attracting media attention and more interest in the satellite industry. Lastly, complementors provide \textit{complementary value} to focal technology producers. Without complementary services, potential usages of the focal product cannot be fully realized. For example, satellite operators can pay a high market price to purchase a satellite. Yet, operators cannot use the satellite for communication, navigation, or any other purposes without having a launch vehicle to place the satellite into space.

\textbf{Contributions}

This paper has three intended contributions. First, it begins to extend the industry evolution theory and helps to overcome some of the limitations of the life cycle approach. Previous studies have mostly focused on explaining evolution from the perspective of technology performance and customer demands (Abernathy & Clark, 1985; Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Christensen, 1997). Few studies have examined the influences of complementors, customers, and component providers in the innovation ecosystem (Adner & Kapoor, 2016; Ethiraj, 2007; Henderson, 1995; Jacobsson & Bergek). This paper uses a structural approach and considers all players in the innovation ecosystem. Results show that while performance of the focal technology is an important factor, its effect becomes insignificant after controlling for the influences of complementors and customer demands. These findings highlight that technology development is not an independent event by the focal firm. Without
necessary complementary service (Stieglitz & Heine, 2007) and demands from customers, technology improvements cannot realize their full potential in the market.

Second, this paper fleshes out the roles of complementors, customers, and focal technology producers during industry emergence. Focal technology producers provide discontinuous technologies and introduce dominant designs that trigger the emergence and growth of an industry. Complementors provide products and services without which the focal technology cannot deliver its value to customers. Results show that without enough launch opportunities, the successful demonstration of the modern small satellite technology did not increase the number of new entrants. Without launch vehicles with enough payload capacities, larger satellites with more capabilities cannot be widely used in the beginning of the satellite industry. Customers apply the focal technology to different functional areas. Therefore, customers’ capabilities in utilizing the focal technology also influence the output and sales level of the focal technology. Results show that before satellite operators had developed data processing technologies, the limited application of small satellite technology has constrained its output and sales level.

Lastly, results of this paper also shed light on how the role of each actor changes as the industry evolves. Findings show that complementors play the most important role in the emergence stage, focal technologies are most critical in the growth and shakeout stage, and customer demands are essential in the later stages and in the beginning of new industry lifecycles. During the emergence stage, having complementary services is one of the necessary conditions for novel technologies to realize their full performance potential. However, as the industry evolved, even without all the necessary complementary service, alternative services such as launching as secondary payloads have been developed. Thus, the requirement of having
dedicated small satellite launch vehicles could be relaxed. In this stage, addressing the changing customer demand becomes the most important factor for new technologies to supplant the old ones. Therefore, findings of this paper also provide implications for firms developing technologies in different stages of the industry lifecycle. Firms should have a different innovation focus depending on the current stage of industry evolution.

**Limitations**

Several limitations ought to be kept in consideration, which also provide avenues for future research. Due to data limitations, I was unable to directly measure performance of large versus small satellites. There is no single measure for satellite performance, as each satellite was designed for a different application purpose based on different customer requirements. Future studies could focus on a particular type of satellite (such as an earth observation satellite) and use more specific performance metrics to compare the performances of large and small satellites. In addition, I did not explicitly examine the role of component providers in the ecosystem. Indeed, satellites are complex systems that involve many components from different suppliers. Future studies could incorporate the role of power system providers, since the power system is one of the most important and the heaviest components of satellites.


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Table 4-1  Key Stages in the Industry Life Cycle

<table>
<thead>
<tr>
<th>Competitive Focus</th>
<th>Emergence</th>
<th>Growth</th>
<th>Mature</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Technology</strong></td>
<td>• Product Innovation</td>
<td>• Process Innovation</td>
<td>• Cost Reduction</td>
</tr>
</tbody>
</table>
|                   | • Primitive design, no well-defined criteria  
|                   | • Manufactured on comparatively unspecialized machinery  
|                   | • Lots of variation of the product, many competition versions;  
|                   | • Product volume is low | • Emergence of a dominant design, more standardization  
|                   | | • Decrease in product innovation, mostly refinement, increase in process innovation  
|                   | | • Have more refined manufacturing techniques  
|                   | | • New entrants account for higher percentage of product innovation;  
|                   | | • Output level grows rapidly | • Mostly incremental innovation  
|                   | | | • Manufacturing reaches a relatively advanced degree of refinement  
|                   | | | • Markets grow at a predictable rate |
| **Producers**     | • Many firm entries producing different variants of the product  
|                   | • High levels of uncertainty | • Shakeout in the number of producers, number of producers declines despite continued growth in industry output  
|                   | | • Less uncertainty | • Stable number of firms  
|                   | | | • Low levels of uncertainty |
| **Customers**     | • High levels of uncertainty about user preferences (even among users) | • Market definition is sharpened | • Very clear user preferences, clear market definitions |
Table 4-2 Chronology of Events

<table>
<thead>
<tr>
<th>Year</th>
<th>Key Event</th>
<th>Background and Implication</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1957 to Mid-1960s First Industry Cycle: Emergence Stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1957</td>
<td>First small and artificial earth satellite Sputnik 1 launched</td>
<td>Beginning of the satellite industry development, proving that an orbiting spacecraft could survive in the hostile environment of space</td>
</tr>
<tr>
<td>1958</td>
<td>US launched the first satellite Explorer 1</td>
<td>The Space Race</td>
</tr>
<tr>
<td>1960</td>
<td>First launch of two satellites by one launcher</td>
<td>The Solrad Model was a dummy version of the Solrad / Grab satellite launched to test the dual launch with the Transit 1B satellite. First tandem satellite launch. Multiple satellite and &quot;piggyback&quot; launches are the current method of getting small satellites into orbit</td>
</tr>
<tr>
<td>1961</td>
<td>First amateur radio satellite OSCAR 1 was launched</td>
<td>A key application of small satellite</td>
</tr>
<tr>
<td>1962</td>
<td>First Kosmos (Zenit-2) satellite was launched</td>
<td>The Kosmos (Zenit-2) satellite was one of the first few dominant designs of early satellites; the same design has been applied in more than 80 satellites since 1962</td>
</tr>
<tr>
<td>1963</td>
<td>First geosynchronous communications satellite Syncom 2 was launched</td>
<td>Demonstrated that satellites could be successfully launched into geosynchronous orbit and operated there for extended periods of time</td>
</tr>
<tr>
<td><strong>Mid-1960s to 1981 First Industry Cycle: Growth/Shakeout Stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-1960s</td>
<td>Surge in launches with larger and more complex commercial satellites such as communication satellites</td>
<td>Testing and developing technologies; failures often occur and were acceptable. Larger and more capable launch vehicles were developed</td>
</tr>
<tr>
<td>Year</td>
<td>Key Event</td>
<td>Background and Implication</td>
</tr>
<tr>
<td>------</td>
<td>-----------</td>
<td>---------------------------</td>
</tr>
<tr>
<td>1969</td>
<td>Radio Amateur Satellite Corporation (AMSAT) was formed.</td>
<td>A group of amateur radio operators have a common interest in building, launching, and communicating with others through non-commercial Amateur Radio Satellites. Successfully launched more than 60 satellites over the years. One of the first pioneering small sat organizations to build, launch and operate experiential satellites. Foundation laid for many of the commercial satellite technologies today</td>
</tr>
<tr>
<td>1977-1987</td>
<td>Small satellite doldrums</td>
<td>Space technology matures; launch of larger commercial satellites begins; no longer willing to afford risks. Smallsats as secondary payloads could cause potential risks to the primary payloads, and thus had very limited launch opportunities</td>
</tr>
<tr>
<td>1981 to Early 2010s Second Industry Cycle: Continued Growth and Shakeout</td>
<td>1981</td>
<td>First modern microsatellite UoSat-1 successfully launched</td>
</tr>
<tr>
<td>1987</td>
<td>Inception of the Utah State SmallSat conference and the “Meeting the Lightweight Satellite Systems” conference</td>
<td>Showed increased interest in smallsat technologies and the need to form a community. Signaled the end of the doldrums and the bringing together of a smallsat community</td>
</tr>
<tr>
<td>1990s</td>
<td>Developing the concept of fully commercial systems</td>
<td>Commercial expansion of university-based satellite development capability</td>
</tr>
<tr>
<td>early 1990s</td>
<td>Establishment of large commercial communication smallsat constellations such as Iridium and Orbcomm</td>
<td>Increased use of small satellite technologies</td>
</tr>
<tr>
<td>1992</td>
<td>The terms microsatellites and nanosatellites originated at the Centre of Satellite Engineering Research at the University of Surrey</td>
<td>Satellites were not classified according to size before</td>
</tr>
<tr>
<td>Year</td>
<td>Key Event</td>
<td>Background and Implication</td>
</tr>
<tr>
<td>------</td>
<td>-----------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>1999</td>
<td>Introduction of CubeSats, which set an industry standard for smallsats</td>
<td>A concept was developed that would not only allow university groups to rapidly implement a small space mission, but also to ensure that the chances of obtaining a space launch as a secondary passenger were maximized. Standardizing interfaces and prohibiting or limiting design aspects that could be potentially hazardous and would reduce the chances of being launched next to larger, more expensive spacecraft; CubeSats offer a fast and affordable way for a wide array of stakeholders to be active in space and allow for a fast innovation cycle.</td>
</tr>
<tr>
<td>1999</td>
<td>UoSat-12 launched; heralded a new era in smallsat earth observation</td>
<td>Use of available commercial off-the-shelf (COTS) components demonstrates advanced high-resolution multispectral and panchromatic Earth observation payloads, low Earth orbit microwave digital communications, as well as a number of innovative propulsion and attitude control technologies.</td>
</tr>
<tr>
<td>2003</td>
<td>First CubeSats launched as secondary payloads on Eurocket launch</td>
<td>Six projects hitched a ride on a Russian Eurocket launch vehicle for about $40,000 per cube.</td>
</tr>
<tr>
<td>2007</td>
<td>US National Science Foundation starts CubeSat Program</td>
<td>The program focuses on space weather and encourages the use of CubeSats as a way to get more data more quickly than multimillion-dollar satellite missions.</td>
</tr>
</tbody>
</table>

Early 2010s to Present: Second Industry Cycle: New Emergence Stage

<table>
<thead>
<tr>
<th>Year</th>
<th>Key Event</th>
<th>Background and Implication</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>NASA started the CubeSat Launch Initiative – each year offers a free ride to a dozen or more successful applicants as hitchhikers on primary loads</td>
<td>Provide more launch opportunities to small satellites</td>
</tr>
<tr>
<td>2010</td>
<td>Planet Labs founded by three former NASA scientists; launched an earth imaging system</td>
<td>A leading firm focusing on novel applications of small satellites</td>
</tr>
<tr>
<td>2013</td>
<td>First PhoneSat successfully launched</td>
<td>Ongoing NASA project, building nanosats using unmodified consumer-grade off-the-shelf smartphones and launching them into low earth orbit</td>
</tr>
</tbody>
</table>
### Table 4-3 Most Frequently Used Satellite Designs

<table>
<thead>
<tr>
<th>Satellite Name</th>
<th>First Successful Launch</th>
<th>Total Number of Launches</th>
<th>Key Application Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kosmos (Zenit-2)</td>
<td>1962</td>
<td>81</td>
<td>Reconnaissance</td>
</tr>
<tr>
<td>KH-4A (Corona, OPS)</td>
<td>1963</td>
<td>52</td>
<td>Reconnaissance</td>
</tr>
<tr>
<td>Kosmos 36 (DS-P1-Yu)</td>
<td>1964</td>
<td>79</td>
<td>Calibrate space surveillance and early warning radars</td>
</tr>
<tr>
<td>Molniya</td>
<td>1964</td>
<td>162</td>
<td>Communication</td>
</tr>
<tr>
<td>Kosmos (Strela-1M)</td>
<td>1970</td>
<td>368</td>
<td>Military communication</td>
</tr>
<tr>
<td>Kosmos (Tselina-D)</td>
<td>1970</td>
<td>69</td>
<td>Electronic intelligence</td>
</tr>
<tr>
<td>Kosmos (US-K)</td>
<td>1972</td>
<td>86</td>
<td>Early warning</td>
</tr>
<tr>
<td>Kosmos (Parus)</td>
<td>1974</td>
<td>99</td>
<td>Navigation, data relay</td>
</tr>
<tr>
<td>Kosmos (Zenit-6U)</td>
<td>1976</td>
<td>97</td>
<td>Reconnaissance</td>
</tr>
<tr>
<td>Kosmos (Yantar-4K2)</td>
<td>1981</td>
<td>81</td>
<td>Reconnaissance</td>
</tr>
<tr>
<td>Space Transportation System (STS)</td>
<td>1981</td>
<td>135</td>
<td>Manned spacecraft</td>
</tr>
<tr>
<td>Kosmos (Uragan)</td>
<td>1982</td>
<td>87</td>
<td>Navigation</td>
</tr>
<tr>
<td>Kosmos (Strela-3)</td>
<td>1985</td>
<td>143</td>
<td>Military communication</td>
</tr>
<tr>
<td>Progress-M</td>
<td>1989</td>
<td>67</td>
<td>Carry propellant and cargo</td>
</tr>
<tr>
<td>Iridium</td>
<td>1997</td>
<td>98</td>
<td>Mobile communication</td>
</tr>
<tr>
<td>Globalstar</td>
<td>1998</td>
<td>97</td>
<td>Mobile communication</td>
</tr>
<tr>
<td>Flock</td>
<td>2014</td>
<td>127</td>
<td>Earth Observation</td>
</tr>
<tr>
<td>Variable Name</td>
<td>Mean</td>
<td>S.D.</td>
<td>Min</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-------</td>
<td>-------</td>
<td>------</td>
</tr>
<tr>
<td>1 SmallSat mkt share</td>
<td>0.347</td>
<td>0.138</td>
<td>0.164</td>
</tr>
<tr>
<td>2 SmallSat mkt share t-1</td>
<td>0.342</td>
<td>0.133</td>
<td>0.164</td>
</tr>
<tr>
<td>3 Smallsat contractors t</td>
<td>0.419</td>
<td>0.144</td>
<td>0.174</td>
</tr>
<tr>
<td>4 Smallsat contractors t-1</td>
<td>0.414</td>
<td>0.141</td>
<td>0.174</td>
</tr>
<tr>
<td>5 Smallsat LV t</td>
<td>0.327</td>
<td>0.136</td>
<td>0.152</td>
</tr>
<tr>
<td>6 Smallsat LV t-1</td>
<td>0.327</td>
<td>0.137</td>
<td>0.152</td>
</tr>
<tr>
<td>7 Launch failure t</td>
<td>0.119</td>
<td>0.137</td>
<td>0.007</td>
</tr>
<tr>
<td>8 Launch failure t-1</td>
<td>0.119</td>
<td>0.138</td>
<td>0.007</td>
</tr>
<tr>
<td>9 Piggyback launch</td>
<td>0.479</td>
<td>0.17</td>
<td>0</td>
</tr>
<tr>
<td>10 Piggyback launch t-2</td>
<td>0.472</td>
<td>0.165</td>
<td>0</td>
</tr>
<tr>
<td>11 Smallsat operators t</td>
<td>0.432</td>
<td>0.199</td>
<td>0.107</td>
</tr>
<tr>
<td>12 Smallsat operators t-1</td>
<td>0.426</td>
<td>0.199</td>
<td>0.107</td>
</tr>
</tbody>
</table>

n=57; Correlations significant at 5% are shown in bold
### Table 4-5 Results of Time Series Analysis (1957-2015)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SmallSat Mkt Share</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.493**</td>
<td>0.460**</td>
<td>0.623**</td>
<td>0.257</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
<td>(0.135)</td>
<td>(0.117)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>% of smallsat manufacturers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.230+</td>
<td></td>
<td></td>
<td>0.184</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td></td>
<td></td>
<td>(0.208)</td>
</tr>
<tr>
<td>( t-2 )</td>
<td>0.097</td>
<td></td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td></td>
<td>(0.195)</td>
<td></td>
</tr>
<tr>
<td>% of smallsat LV</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.402*</td>
<td></td>
<td>0.211</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.186)</td>
<td></td>
<td>(0.232)</td>
<td></td>
</tr>
<tr>
<td>( t-2 )</td>
<td>0.060</td>
<td>0.275</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.221)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of launch failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.372*</td>
<td>0.371*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
<td>(0.174)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-2 )</td>
<td>0.048</td>
<td>0.035</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.134)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of piggyback launch</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.320*</td>
<td>0.321*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.135)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-2 )</td>
<td>0.048</td>
<td>0.194+</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.110)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of smallsat operators</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-1 )</td>
<td>0.093</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.131)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( t-2 )</td>
<td>0.058</td>
<td>0.194+</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.110)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.035</td>
<td>-0.126+</td>
<td>0.0631*</td>
<td>-0.119+</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.068)</td>
<td>(0.031)</td>
<td>(0.070)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>57</td>
<td>57</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td><strong>R-sq</strong></td>
<td>0.652</td>
<td>0.712</td>
<td>0.633</td>
<td>0.755</td>
</tr>
</tbody>
</table>

\( p<0.10 \) * \( p<0.05 \) **\( p<0.01 \)
Table 4-6 Illustration of How the Innovation Ecosystem Perspective Can Provide Novel Explanations

<table>
<thead>
<tr>
<th>Received Wisdom from the Industry Life Cycle Literature</th>
<th>Irregularities Observed in the Satellite Industry</th>
<th>Explanations from the Innovation Ecosystem Perspective</th>
<th>Novel Theoretical Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td>• New industry emergence is often triggered by discontinuous technologies, and during the emergence stage, there is a large number of new entrants</td>
<td>• The modern small satellite technology was successfully demonstrated in 1981, which marks the beginning of a new industry life cycle. Yet, the number of entrants did not dramatically increase until the late 2010s</td>
<td>• Complementors: A series of launch vehicle failures during the 1980s and 90s reduced the number of launch opportunities for small satellites. The number of new entrants was limited because of lack of launch vehicles</td>
<td>• Even though discontinuous technologies can trigger the emergence of a new industry, the number of new entrants may not increase if there are obstacles in finding complementary services</td>
</tr>
<tr>
<td>• During industry emergence, different competitive designs exist on the market, and technologies with best performances will win the competition and have higher market share</td>
<td>• During the emergence of the satellite industry, while large satellites clearly had performance advantage compared to small satellites, small satellites had higher market share in the beginning of the satellite industry</td>
<td>• Complementors: During the late 1950s, launch vehicles had limited payload capacity. Even though large satellites could offer superior performance, they could not be successfully launched until launch vehicles with more payload capacities were developed</td>
<td>• Even though the performance of a focal technology could influence its market share, a technology cannot win the market competition if complementary services have not been developed</td>
</tr>
<tr>
<td>• The establishment of a dominant design marks the end of the emergence stage and the beginning of the growth stage. During the growth stage, there is growing market demand around standardized products, and the output level increases</td>
<td>• The dominant design of small satellites – CubeSat was established in 1999, which marks the beginning of the growth stage. Yet, the market demand and output level for small satellite did not increase until early 2010s</td>
<td>• Customers: During the 2000s, the main operators of small satellites remained to be universities and amateur radio stations. Small satellites were mainly used for scientific and experiment purposes. The small satellite technology did not become widely used until satellite operators developed technologies such as big data processing to enable more commercial applications</td>
<td>• Even though the emergence of dominant designs is an important feature of the growth stage, demand and output level for these standardized product may not increase until customers have also developed technologies to better apply and use them</td>
</tr>
</tbody>
</table>
Figure 4-1 Total Number of Satellites Successfully Launched (1957-2015)

- **First Industry Cycle**
  - Emergence of the first dominant design, the Kosmos (Zenit-2) satellite
  - Growth/Shakeout

- **Second Industry Cycle**
  - The first modern smallsat was successfully launched
  - Emergence of first smallsat dominant design, the CubeSat
  - Continued shakeout
  - New Emergence

Figure 4-2 Number of Small and Large Satellites Successfully Launched (1957-2015)

- **Small Satellite**
- **Large Satellite**
Figure 4-3 Number of New Satellite Manufacturer Entries Per Year (1957-2015)


Emergence
Growth/Shakeout
Continued Growth/Shakeout
New Emergence
Figure 4-4 The Innovation Ecosystem of the Satellite Industry

Components
- Power System
- Thermal Control
- Tracking, Telemetry, Command and Monitoring
- Ground Surveillance and Communication
- Stabilization and Pointing System
- Launch Vehicle
- Satellite Operator
- Customers
- Focal Technology

Figure 4-5 Key Events in the Innovation Ecosystem and Changes in the Small Satellite Market Share

Note:
Key events related to complementors are shown in red;
Key events related to technology producers are shown in black;
Key events related to customers are shown in green;
+ indicates an event that facilitate the use of small satellite technologies;
- indicates an event that inhibits the use of small satellite technologies;

- Satellite operators mostly government agencies
- LVs with higher payload capacities developed
- A series of LV failures
- Satellite operators expanded to universities, amateur radio stations, and a few commercial organizations
- Demonstration of modern small sat technology
- Multiple satellites (more than 20) on one LV
- Introduction of Small Sat Dominant Design
- A large number of commercial operators enter
Company names are shown in boxes; The products and services they provided are shown in blue italics; 
| indicates component suppliers; | indicates complementary service providers; | indicates focal producers; | indicates customers;
Figure 4-8 Launch Failure Rate

Figure 4-9 Number of Launch Vehicles Available for Large and Small Satellites
Figure 4-10 Number of Large and Small Satellite Operators
CHAPTER 5: CONTRIBUTIONS AND IMPLICATIONS

In this dissertation, I examined the nature and role of firm capability with a focus on absorptive capacity and technological competence. In Paper One, I reviewed and synthesized studies on firm capability by focusing AC as a critical capability that shapes external learning (Cohen & Levinthal, 1990, 1994; Lane, Koka & Pathak, 2006; Zahra & George, 2002). Through an extensive review of conceptualizations, measures, and outcomes of AC, I identified effort, competence, and process as three key aspects of AC. I also identified knowledge generation, innovation generation, and firm performance as three commonly examined outcomes of AC. Using meta-analytical techniques, I examined the relationship between the different aspects of AC and the different outcomes. The review and synthesis of the absorptive capacity literature has provided a distilled understanding of the core of AC and its role and helped to develop cumulative knowledge on this topic. Paper One also informed and shaped my subsequent studies.

Building on insights from the meta-analysis, I examined in Paper 2 how firm capability interacts with other factors and influences innovation choices. With an intra-firm focus, I theorized that managerial cognition shapes firms’ innovation decisions (Barker & Mueller, 2002; Jansen, George, Van den Bosch & Volberda, 2008; Qian, Cao & Takeuchi, 2013) and used CEO experience as a proxy for cognition. Results from the satellite industry showed that CEO’s industry experience moderates the relationship between the firm’s technology capability and innovation choices. Specifically, the main effect of technology relatedness and diversity on innovation choices gets strengthened or weakened based on the relatedness and diversity of CEO experience.

Research shows that firms’ collective innovation decisions could shape the evolution of an industry (Anderson & Tushman, 1990; Klepper, 1996). In the third paper, I shifted the focus
to the industry and explored how the entire innovation ecosystem contributes to industry evolution. I theorized that different actors in an ecosystem played unique roles in shaping the industry. I identified focal technology producers such as satellite manufacturers, complementors such as launch vehicle providers, and customers such as satellite operators as important actors in the innovation ecosystem in the satellite industry. Longitudinal analysis of the satellite industry during the past 58 years showed that the availability of launch vehicles and changing customer demand had critical impacts on the evolution of the industry. Their effects were even stronger compared to the manufacture of satellites.

Collectively, this dissertation improved the conceptual coherence of the capability construct and highlighted the importance of considering other factors when studying its effect. Results of this dissertation showed that the effect of firm capability is dependent on the specific conceptualization and measurement used and the outcome examined. While firm capability is a commonly used predictor for innovation outcomes, results of my dissertation showed that its main effect became insignificant when the interaction term of firm capability and CEO experience was added to the model. When examining the evolution of an industry, the individual effect of focal technology producers became insignificant when variables related to other actors in the innovation ecosystem were added to the model. Overall, my dissertation showed that the effect of firm capability varied by its conceptualization, its measure, its outcome, and its interaction with other internal and external contingencies. Therefore, this dissertation provided a basis for future scholars to be explicit about the specific aspect of firm capacity and illustrated the importance of incorporating managerial cognition and innovation ecosystem when studying the role of firm capability.
The three papers of my dissertation uniquely contributed to literatures on firm capability, innovation decision-making, and industry evolution. Table 5-1 illustrates the contributions and implications of each paper. Within the capability literature, the distillation of the AC literature and illumination of the core aspects of AC provided a much-needed conceptual coherence on AC as one key aspect of firm capability (Lane et al., 2006; Volberda, Foss & Lyles, 2010). Paper One brought conversation of AC to its core, and showed differential effect of AC on organizational outcomes. In addition, it underscored the importance of specifying the underlying mechanisms and discussed how the measurements corresponded to those mechanisms. Paper One thus has several implications for future research: future scholars need to go deeper into the conceptualization of AC and use appropriate measures that match with their conceptualization; they also need to be clear on the AC aspect they focus on, and the AC outcome they examine because the effect of AC is dependent on these choices. Overall, this paper provided a strong basis for cumulative knowledge development and for more rigorous empirical research on the important topic of AC.

[Insert Table 5-1 about here]

In Paper Two, I offered insights on how firms make innovation choices, which are important antecedents of innovation performance (Kaplinsky, 2000; Talke, Salomo & Rost, 2010). Innovation is crucial for firm survival and growth (Santos & Eisenhardt, 2009), and firms have different options to pursue innovation. Paper Two explicated two major options—product and application based innovations—and determinants of such options. I also demonstrated that different aspects of technological capability and CEO experience work differently for product versus application innovations. Findings about the significant interaction effects between firm capability and CEO experience underscored the importance of simultaneously considering these
two drivers of innovation choices. Examination of both unique and joint effect of capability and cognition is necessary in order to understand innovation choices made by the firm. Future studies could continue to examine distinct aspects of capability and cognition and further investigate the potential complementarities between these two factors. In addition, while I used patent-based measures and CEO experience as proxies for capability and cognition, future studies could develop more precise and thorough ways of capturing capability and cognition.

Paper Three illuminated key limitations of the life cycle approach to industry evolution and began to extend the industry evolution theory by offering ecosystem explanations. Previous studies have mostly focused on the perspective of focal technology producers in explaining industry evolution (Abernathy & Clark, 1985; Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Christensen, 1997). I argued that the traditional models of industry evolution that emphasize performances of focal technologies are possibly inadequate to explain the emergence and growth of new technology-intensive industries such as the small satellite industry. I also provided illustrative evidence to support my arguments on the unique role of different actors in the ecosystem. Paper Three thus underscored the need to consider the entire ecosystem, and how each actor played separate and collective roles in influencing industry evolution. Future studies could further investigate the ways through which values are created and captured in the innovation ecosystem.

In addition, findings from Paper Three revealed that the relationship among different actors in the innovation system is interdependent and complex: many incumbent firms enter into a wide range of emerging industries and the product offerings of each individual firm change frequently. These observations suggested that the traditional way of categorizing firms into specific industries based on whom they compete with or what products they offer might not work
in the certain industry settings. For example, it is increasingly difficult to categorize companies like Google into a specific industry. By building on the ideas developed in this dissertation, future studies could develop richer explanations of how a group of technologies and firms emerge and evolve.

Overall, in this dissertation, I reviewed and synthesized the effect of firm capability by focusing on the AC literature. I further investigated and showed how capability interacts with managerial cognition and innovation ecosystem in predicting innovation choices and industry evolution. The small satellite industry offered me a novel and unique context to understand the nature of firm innovation and industry evolution. I observed that the small satellite industry had attracted many entrants with diverse sets of capabilities; companies pursued a diverse range of innovations; many actors provided very unique offerings; yet, they were also highly interdependent with each other, and they found a way to collectively create value. These observations have motivated me to better understand how firms made innovation choices in this industry, and how the industry evolved. While this dissertation offered many novel implications, results of Paper Two and Three were based on investigation of a single industry. Future scholars could continue to explore this prominent research avenue, and examine innovation choices and evolution patterns in other industry settings.
REFERENCES


### Table 5-1 Summary of Contributions and Implications

<table>
<thead>
<tr>
<th>Literature Stream</th>
<th>Contributions</th>
<th>Implications</th>
</tr>
</thead>
</table>
| **Absorptive Capacity** | • Clarifies conceptual ambiguity in the AC literature, brings conversation of AC to its core, and shows differential effect of AC on organizational outcomes  
• Provides a strong basis for cumulative knowledge development on AC | • Researchers need to go deeper into conceptualization of AC and use appropriate measures that match with their conceptualization  
• Researchers need to be clear on the AC aspect they focus on and the AC outcome they examine, because the effect of AC is dependent on these choices |
| **Innovation** | • Offers insights on how firm make innovation choices, which is an important antecedent of innovation performance  
• Underscores the importance of both capability and cognition in explaining innovation-related outcomes, and highlights the need to simultaneously consider these two factors when predicting innovation | • Examination of both unique and joint effect of capability and cognition is necessary in order to understand innovation choices made by the firm  
• Underscores the potential role of cognition and the need develop more precise and thorough ways of capturing cognition and capability |
| **Industry Evolution** | • Illustrates that the traditional models of industry evolution that emphasize performances of focal technologies are possibly inadequate to explain the emergence and growth of new technologically intensive industries  
• Underscores the need to consider the entire ecosystem, and how each actor plays separate and collective roles in influencing industry evolution | • Understanding of industry evolution requires consideration of the entire ecosystem of actors  
• Future research could investigate how unique value is created and captured by different actors in the innovation ecosystem |