EXAMINING HETEROGENEITY IN ENTREPRENEURIAL STRATEGIES IN AN EMERGING HIGH-TECH INDUSTRY

The Role of Founder Experience and Knowledge Structure in the Lithium-Ion Battery Industry

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ABSTRACT

In emergent high technology industries, entrepreneurs and their new ventures play a critical role in enhancing economic growth. In these industries, we can easily see some new ventures grow more rapidly to outperform their competitors. However, looking beyond the surface, new ventures' growth path is idiosyncratic. More specifically, when growing, new ventures pursue different paths in terms of 1) which technologies they develop, 2) which products they make, and 3) what markets they enter. The question that has struck me is why high-tech new ventures differ on these key strategic choices. Building on literature on entrepreneurship, strategy, industry evolution, and network, this dissertation tries to answer this important question by focusing on intra-firm factors, more specifically, the individual and structural attributes of new ventures. Types of founder experience and new ventures' knowledge structure are investigated in depth. My three studies, each presented as a separate essay herein, investigate how individual (i.e. founder experience) and structural attributes (i.e. knowledge structure) affect key strategic choices regarding i) product market scope (Wernerfelt and Montgomery, 1988), ii) technological search scope (Katila and Ahuja, 2002), and iii) the types of new products (Sanchez and Mahoney, 1996; Henderson and Clark, 1990), respectively. In each, I discuss the relevant theories, methodology, data sources, results and implications. By investigating intra-firm factors that trigger different entrepreneurial strategies, my dissertation responds to an important call – micro-foundation of strategy formation – thus filling a key gap in the entrepreneurship literature.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

New ventures' growth paths are idiosyncratic. Indeed, when growing, they strategically pursue different paths in several key domains including i) which technologies they develop, ii) which products they make, and iii) what markets they enter. What determines such heterogeneity is clearly one of the most fundamental questions both in strategy and entrepreneurship research. However, existing theory does not adequately explain why new ventures make different strategic choices along their growth paths.

Rather, on one hand, considering the fact that new ventures' strategic decision-making is typically influenced by the founder(s), both entrepreneurship and evolutionary theories have investigated how founders' pre-entry experience shapes new venture performance (Brüderl, Preisendörfer, and Ziegler, 1992; Agarwal, Echambadi, Franco, and Sarkar, 2004). On the other hand, emphasizing the fact that strategic choices regarding technology, product, and market, respectively, have a significant impact on firm-level outcomes such as profits and survival, (Katila and Ahuja, 2002; Eggers, 2014; Dowell, 2006), strategy research has largely examined the systematic linkages between a given growth strategy and its performance implications. Despite voluminous work in these streams of literature, little attention has been paid to examining the determinants of new venture strategies, leaving the process of what constrains or promotes particular strategic choices a black box.

The purpose of this dissertation is to theorize on the origins of firm heterogeneity in the various strategies of new ventures. In this process, I explore internal firm determinants rather than external environmental factors in a context where new ventures are confronted with one identical industry setting characterized by high uncertainty in both technology and market demand. More specifically, my dissertation investigates how both individual and structural attributes inside new ventures promote or constrain key strategic choices regarding i) technology search scope (Katila and Ahuja, 2002), ii) new product choices (Eggers, 2014), and iii) product market scope (Wernerfelt and Montgomery, 1988), respectively.

Among the various types of individual attributes, looking at founder experience as a source of knowledge is key, especially given that new ventures' pre-entry knowledge mainly stems from founder experience. One major part of my dissertation explores how founders' past experiences play a role in shaping new ventures' strategic decision-making process, in particular, demand- (i.e. market) and supply-side (i.e. technology) choices. Meanwhile, among various types of structural features, understanding a new venture's knowledge structure – the relationships among knowledge elements within the knowledge base – is also critical, as these relationships reflect founders' beliefs about which elements of knowledge will work well together to generate new products. The other major part of my dissertation examines how and to what extent a new venture's way of combining knowledge components plays a role in developing new products.

By unpacking the micro-foundation of various types of new venture strategies, my dissertation advances a stream of research suggesting that internal firm-level factors are the main driver of firm-level outcomes (Felin and Foss, 2005). Although some view firm-level capabilities as the locus of firm strategy, because firms consist of the individuals residing within them, research needs to look beyond organizational capabilities and focus on the role that individuals play. In responding to this call, my dissertation highlights the fact that founders and the structures embedded in their shared beliefs about combining knowledge can provide an explanation for why new ventures select different strategies.

Building on entrepreneurship and evolutionary economics, my first essay aims to answer the fundamental question of why new ventures develop different product market scopes by systematically examining the various types of founder experience. This essay mainly argues that new ventures expand or constrain their market scope based on the features of founders' prior experience. More specifically, this first essay delineates the distinctive effect that 1) founder relevant industry experience, 2) founder diverse industry experience, and 3) prior founding experience before entry into a high-tech industry have on the market scope of a new venture over time. The theoretical contribution of this chapter is that it applies a strategic lens to investigate an important but previously unexamined linkage between strategy and entrepreneurship theory – founders' influence on setting the market scope trajectories of new ventures.

While new ventures' search strategies play a crucial role in their innovative performance, little is known about the antecedents of the two major types of search strategies – namely breadth and depth. Drawing on entrepreneurship, knowledge, and search literature, my second essay addresses this gap by examining how the various features of founder experience before entry into the focal industry affect new ventures' technology search strategies or (a new venture's technology search strategy). My main argument is that new ventures with founders whose prior industry experience is 'relevant' to a focal industry are positively related to both breadth and depth search strategies, whereas new ventures with founders whose prior industry experience is 'diverse' are negatively related to both breadth and depth search strategies.

Responding to a call in the realm of innovation literature – namely the need to examine how the structural aspects of a firm's knowledge base can determine the types of new products a venture develops – the third essay turns scholarly attention toward a firm's knowledge base to investigate the effect of its particular structural pattern - knowledge decomposability on two types of new product development – modular and architecture. The main argument of this essay is that variations in the level of knowledge decomposability distinctively affect the two types of new products. More specifically, increasing decomposability of a new venture's knowledge structure is positively associated with modular product development, whereas increasing decomposability has an inverted U-shaped relationship with architectural product development. By distinguishing between those two types of newly developed products, this essay extends a burgeoning literature that examines how the structural patterns of a new venture's knowledge base can affect its product commercialization strategy (Guan and Liu, 2016; Wang *et al.*, 2014; Yayavaram and Ahuja, 2008).

I empirically tested these essays using a unique longitudinal data set in a high-tech industry - global Lithium-Ion Battery (LIB) cell manufacturing ventures founded since the industry's emergence in 1991. This high-tech industry is an ideal setting through which to examine the drivers of new venture strategies because of the product's clear-cut market applications, founders' heterogeneous pre-entry experience, the high-level of patent activities, and the lack of dominant products. In terms of industry life cycle, the LIB cell manufacturing industry is currently in its growth stage, as there is no shake out or dominant technology, and high level of uncertainty.

Because my sample consists of all prospective new ventures within a single industry over the period since its emergence, my research avoids the survival bias that plagues many studies that explore entrepreneurial phenomena (Beckman and Burton, 2008). In addition, another major advantage of my data set is that my empirical approach assesses objective factors via direct collection of founder working trajectories, rather than relying on respondents' subjective memories about their pre-founding experiences (Dencker, Gruber and Shah, 2009; Gruber, 2010; Dencker and Gruber, 2015).

CHAPTER 2: ESSAY ONE

FOUNDING THE FUTURE: THE ROLE OF FOUNDER PRIOR EXPERIENCE ON MARKET SCOPE PATHS OF NEW VENTURES IN THE GLOBAL LITHIUM-ION BATTERY INDUSTRY

Abstract

Founders' strategic choices on market scope play a crucial role in new venture survival. Yet, little is known about how founders' pre-entry experience influences such choices. My study fills this gap by examining how the various features of founder experience before entry into a focal industry affect the market scope trajectories of new ventures in the early phases of an industry's life cycle. An empirical analysis of 84 global entrants in the global Lithium-Ion Battery cell manufacturing industry from 1991-2011 supports my arguments. While new ventures are more likely to expand their market scope when their founders possess prior industry experience that is relevant to the focal industry, they are less likely to expand their market scope when their founders possess prior experience in diverse industries before entry into a focal industry. Moreover, this study shows the value of founding experience in expanding new ventures' market scope.

Keywords: Founder Prior Experiences, Market Scope, Emerging Industries.

Introduction

How a firm determines its market scope is one of the most fundamental questions in strategy research (Hoskisson and Hitt, 1990; Rumelt, Schendel, and Teece, 1994). Prior work has advanced this stream of research by focusing on external factors – changes in demand and market conditions (Hoskisson and Hitt, 1990; Anand and Singh, 1997; Levinthal and Wu, 2010), corporate governance (Hoskisson and Hitt, 1990; Villalonga and McGahan, 2005), institutional relatedness (Peng, Lee, and Wang, 2005), and foreign competition (Wiersema and Bowen, 2008), as well as internal factors – the role of firm resources and capabilities (Silverman, 1999; Tanriverdi and Venkatraman, 2005), the changes in firm resources (Markides and Williamson 1994; Kaul, 2012), and the attributes of firm resources (Helfat and Eisenhardt, 2004; Sakhartov and Folta 2014; Toh 2014) as antecedents of changes in market scope.

Choices about market scope are also of strategic importance for new ventures as these decisions made at entry are likely to set different trajectories for market scope over time (Dencker et al, 2009). Given the prevalence of a nascent form of presence in more than one product line (Stern and Henderson, 2004) or operation in more than one market (Li and Greenwood, 2004) within single industry (Tanriverdi and Lee, 2008), however, little attention has been paid to exploring on the antecedents of market scope in the context of new ventures (Notable exception is Døving and Gooderham, 2008). Considering the different motivations between established firms and new ventures on why they decide to change their market scope, the resource-based view (RBV) through which the scope of established firms have been primarily examined can hardly be applied to investigating the scope of new ventures. While the availability of slack resources and the willingness to share resources among business units are major motivations for established firms to widen their market scope (Chatterjee and Wernerfelt, 1991; Farjoun, 1994), new ventures may rather decide to change their market scope as a way to overcome the lack of internal resources and the liability of newness under uncertain and volatile circumstances (Barroso and Giarratana, 2013). Thus, theorizing on the antecedents of market scope of new ventures is an important area of research to advance the literature.

In the process of theorizing the origins of firm heterogeneity in market scope, an emerging line of research has begun to investigate internal antecedents by positing that a firm's capacity to integrate resources may serve as the driver of new venture market scope (Døving and Gooderham, 2008). However, research needs to go beyond looking a firm's resources simply as the form of knowledge that is collected separately across individuals (Grant 1996, Coff 1997, Felin and Hesterly 2007). Moreover, given new ventures typically lack experiential knowledge within the focal industry, among individuals, founders' past experience plays a critical role in determining new ventures' market scope (Arrow, 1974).

Because setting the market scope is one of the key strategic choices for new ventures (Penrose 1959; Helfat and Eisenhardt 2004), it is obvious that the types of knowledge accumulated from founders' prior experience have a significant impact on widening/constraining their new ventures' market scope. However, we have a lack of understanding on how are the effects of the types of founder pre-entry experience on choosing 'focus' vs 'breadth' market scope strategies in an emerging high-tech industry? Which feature of founder experience is most effective in encouraging ventures to expand their market scope?

Drawing on founder knowledge endowment and strategy literature, this study advances theories on the antecedents of market scope change in the context new ventures by investigating how founders' pre-entry experience shapes market scope paths. To do so, I explore several forms of experience that founders can gain before entering into an emerging industry. Relevant industry experience is defined as experience gained before entry from industries that are closely related to the focal industry (Helfat and Lieberman, 2002). For example, if founders have working experience in the chemicals industry before entry into the Lithium Ion Battery (LIB) industry, I categorize that experience as relevant, since battery manufacture directly involves knowledge of chemicals. This implies that both the LIB industry and chemicals industry are closely related. Next, diverse industry experience captures whether founders worked for a variety of industries before entry into the focal industry (Gruber, 2010). For instance, if founders have broad work experience across the retail, manufacturing, and service industries before entry into the LIB industry, I consider this founder's industry experience to be diverse. Founders are considered as serial entrepreneurs if they possess prior founding experience before entry into the LIB industry (Wright, Robbie, and Ennew, 1997).

The central argument of the paper is that while pre-entry experience in relevant industries fosters broader market scope, pre-entry experience in diverse industries constrains market scope. I also argue that pre-founding experience enables new ventures to expand their market scope over time. I further predict that relevant industry experience is most significant in widening new ventures' market scope compared other forms of founder experience.

I tested these arguments using a unique longitudinal data set – the entire population of global Lithium-Ion Battery (LIB) cell manufacturing ventures founded since the industry emerged in 1991. Because my sample consists of all prospective new ventures within a single industry over 15-year period since its emergence, it avoids the survival bias that plagues many studies that explore entrepreneurial phenomena (Beckman and Burton, 2008). In addition, my empirical approach assesses objective factors via direct collection of founder working trajectories, rather than relying on respondents' subjective memories about their pre-founding experiences (Dencker, Gruber and Shah, 2009; Gruber, 2010; Dencker and Gruber, 2015).

My study contributes to the literature in several ways. First, the study advances entrepreneurship literature by explaining why founders conceive of decision making differently even within the same environment. Second, the study advances research that has largely examined the antecedents of changes in market scope by introducing founders' prior experience as another key driver of market scope of new ventures. Third, it complements industry evolution literature by not only furthering inquiries into the effect of pre-entry experience on post-entry strategic choices, but also deconstructing coarse information on firm-level pre-entry capabilities into the delicate details of founder-level prior experience (Qian, Agarwal, and Hoetker, 2012; Kapoor and Furr, 2015).

Theory and Hypotheses

I begin with a brief overview of the constructs derived from the theories and characteristics of my empirical context. Following Li and Greenwood (2004), I define market scope expansion as the decision to expand a firm's operation into more than one market within a focal industry. Thus, my study does not consider market scope expansion across industries (Hoskisson and Hitt, 1990; Rumelt, et al, 1994).

The empirical context of the LIB industry represents the early and growth phases of the industry's life cycle, given not many exit events have occurred since its emergence in 1991. Since the LIB industry is technology-intensive, these phases are characterized by high uncertainty in both technology and market demand (Abernathy and Utterback, 1978; Tushman and Anderson, 1986). It is also a period characterized by a lack of industry-specific knowledge (Gort and Klepper, 1982), by multiple competing technologies and no consensus concerning the dominant design (Suarez and Utterback, 1995), Thus, a severe competition exists among three distinctive battery technologies of lithium-ion, lead-acid, and nickel batteries (Battke et al, 2013), and so far a leading battery technology has yet emerged in any of the investigated market applications.

Therefore, founders in such a high-risk setting may face greater challenges in market scope expansion as consumer tastes rapidly change or as substitute products become available (Miller, 1992). Yet, such a risky setting should also offer new ventures the opportunity to grab higher economic payoffs by expanding the market scope through new product development of their new products, as they will find it easier to upset existing patterns of competition (Miller, 1992). Likewise, new ventures may take advantage of unstable or deteriorating customer relationships among incumbent firms by delivering superior products to other markets in order to rapidly gain market share (Wiklund and Shepherd, 2003). In sum, although the market scope expansion activities of new ventures are inherently risky, new ventures have the chance to exploit opportunities by expanding their market scope. Taking this a step further, I argue that the difference in the types of knowledge that accrued from their prior experience before entry into a focal industry matters for successful opportunity exploitation (Beckman and Burton, 2008; Fern, Cardinal, and O'Neill, 2012), since founders' pre-entry experience exerts a significant influence in the earlier phases of the industry life cycle where industry-specific knowledge is not yet established (Bayus and Agarwal, 2007).

My hypotheses delineate the features of founders' pre-entry experience that underlie the way they decide to set the market scope expansion paths of their new ventures. I suggest that factors that will increase market scope include founder relevant industry experience and founding experience before entry into a focal industry. In contrast, diverse industry experience before the entry will decrease market scope.

Founder Relevant Industry Experience

When individuals face a strategic choice, the most basic factor influencing their decision is the knowledge they have gained from prior experiences (Higgins, 1996). Drawing on extant research, it is evident that during new venture founding entrepreneurs' decisions are also constrained by their prior experience. One type of prior experience that has been of considerable interest to scholars studying entrepreneurship is founder pre-industry experience before entry into a focal industry (Delmar and Shane, 2006; Qian et al, 2012).

Prior literature on cognitive psychology has examined how founder pre-industry experience affects the choice of industries where they found new ventures. (Fern et al, 2012; Edmondson, Bohmer, and Pisano, 2001). This research argues that as founders' knowledge is formulated and accumulated around their pre-industry experience, founders tend to delimit their strategic options of possible entry to industries when founding new ventures. As a result, founders are more likely to choose industries that are relevant to their past industry experience. For example, founders with chemistry industry experience are more likely to found new ventures in the battery industry compared to those with food industry experience.

After founders enter a focal industry that is relevant to their past industry, they can enjoy several benefits that those lacking this type of experience cannot. First, rich knowledge about the focal industry context provides founders with advantages when trying to understand the content of knowledge as well as the underlying links between knowledge components. This benefit helps them perceive cues in case environments and technologies are shifting (Ericsson, 2006). For example, in my empirical context, founders from battery-related industries know that Lithium-Ion Battery (LIB) cells are composed of four elements – cathode, anode, separator, and electrolytes, and they also understand that the chemical combination of cathode and anode materials generates electrical energy. Second, relevant founder experience provides a tacit understanding of the products, processes, and technologies used in a focal industry, the industry's leading suppliers and distributors, and the industry's competitive landscape (Cooper, Gimeno-Gascon, and Woo., 1994; Helfat and Lieberman, 2002). By engaging in less "trial and error" learning (Brüderl, Preisendörfer, and Ziegler, 1992), they are more capable of recognizing potential new market opportunities in the industry than those without such experience. Third, founders with relevant industry experience garner first-hand experience regarding the competitive rivalry that can potentially arise when they expand their market scope (Eisenhardt and Martin, 2000). As a result, these founders know that they will constantly have to defend their firms' competiveness and will therefore exploit riskier opportunities and be more proactive in expanding their market scope through new product development. Fourth, drawing on the relational view, another stream of literature suggests that founders with relevant industry experience are more likely to garner a higher level of legitimacy than those without such experience when entering a focal industry, due to pre-existing social ties with key stakeholders including suppliers, distributors, and investors. As they can more smoothly overcome challenge of the liability of newness (Granovetter, 2002) through social networks, such founders also feel less pressure to mobilize resources as they have higher creditability from external stakeholders, and therefore can more easily navigate potential new markets.

Furthermore, the positive association between founder relevant industry experience and market scope expansion is more pronounced at the early stages of industry life cycle. Because industry-specific knowledge has not been developed in these stages, the industry is characterized by uncertainties in technology and market demand. As industry-specific knowledge develops after a dominant design is set, product features become largely predictable (Abernathy and Utterback 1978). After that point, pre-entry experience from relevant industries are less likely to fit the norms of the focal industry. Hence, the value creation potential and relevance of pre-entry experience decreases over time (Bayus and Agarwal 2007; Ganco and Agarwal 2009).

Taken together,

Hypothesis 1a: New ventures with founders that have experience in technologically related industries will have broader product market scope than those without such experience.

Founding Experience

One of key benefits of a broad market scope strategy is a venture's ability to hedge their bets about which of their products will meet consumer's preferences (Sorenson, 2000). Because of the lack of dominant designs in the early stages of the industry life cycle, this is particularly important in emerging industries. However, for new ventures, this benefit can be offset by the fact that broader product lines require more resources than narrower lines (Carroll, 1984; Romanelli, 1989). New ventures are likely to encounter congestion because in their infancy they have to engage in a wide range of internal and external organizing activities during firm creation other than seeking for new market opportunities. (Gimeno, Folta, Cooper, and Woo, 1997). More specifically, new ventures need to develop new firm competencies, establish business functions, train employees, and solidify relationships both within the firm and between the firm and its stakeholders (Stinchcombe, 1965; Henderson, 1999). Given their limited financial resources, the more breadth that a firm attempts to include, the more their resources must be devoted toward the activities described above, which are likely to be delegated to founders.

Founders with founding experience before entry into a focal industry have a better understanding of the scope and content of their firm creation activities, as they already learned which business functions, organizational processes, roles and relationships have to be established when founding a new venture (Lazear, 2005). Moreover, they will benefit from having a clearer idea of which tasks need to be prioritized among the manifold activities that can be undertaken during new firm creation (Gifford, 1992). Furthermore, with the possession of knowledge on key organizational routines and functions, they can set up and run their new ventures in a more effective way (Cooper et al., 1994). As a result, new ventures founded by serial entrepreneurs are better able to manage costs, and thus manage to allocate more resources toward broadening their market scope than those with novice entrepreneurs.

Thus,

Hypothesis 1b: New ventures with founders that have prior founding experience will have broader product market scope than those without such experience.

Relevant Industry Experience vs. Founding Experience

I examined the role of two types of founder experience that have been significant in prior entrepreneurship literature – relevant industry and founding experience. Although my arguments highlight that both relevant industry and founding experience can be beneficial to new ventures when they expand their market scope over time, I do not specifically address which of the two types is more useful – *"*an omission that touches on debates in the literature regarding which type of experience is most effective in entrepreneurial endeavors*"* (Dencker and Gruber, 2015:pp.7:47-49).

Because choices regarding market scope primarily depend more on knowledge about technology and markets rather than knowing how to manage core business activities such as understanding the managerial relevance of changes in the industry (Miller, 1998), I argue that relevant industry experience matters more in market scope expansion. As I mentioned above, founder relevant industry experience provide knowledge about the focal industry context and a tacit understanding of the products, processes and technologies used in a focal industry. Founder relevant industry experience thus allows new ventures to establish an aggressive mindset. In other words, such founders acknowledge the fact that new ventures will constantly have to defend their firms' competiveness, and they will therefore be more proactive in expanding their market scope through new product development. In contrast, founding experience is often a defensive mechanism through which new ventures realize the benefits of market scope expansion by managing potential costs, as increased inventory costs (Kekre and Srinivasan, 1990), higher design costs (Bayus and Putsis, 1999), and increased complexity in manufacturing or assembling products leading to greater downtimes (Anderson, 1995; Mac-Duffie, Sethuraman, and Fisher, 1996).

Moreover, considering my empirical context - the early phases of an emerging high-tech industry where industry-specific knowledge has not yet been developed, relevant industry experience can be key for new ventures looking to create value. (Hoetker, 2004). The preceding arguments suggest that founder relevant industry experience will exert greater influence on the market scope expansion of new ventures over time.

Thus,

Hypothesis 1c: Technology related industry experience will has a greater positive influence on breadth of product market scope than prior founding experience.

Diverse Industry Experience

The literature on cognitive complexity, defined as an individual's 'capacity to construe social behavior in a multidimensional way' (Bieri, 1966: 185), posits that cognitive complexity enables 'differentiation— the ability to perceive several dimensions in a stimulus array—and integration—the development of complex connections among the differentiated characteristics' (Bartunek, Gordon, and Weathersby, 1983: 274). Individuals with greater cognitive complexity will consider a greater number of options in their decision-making process before committing to a single approach (Goodwin and Ziegler, 1998). For example, Gruber (2010) found that founders' work experience across various industrial domains (e.g., retail, manufacturing, service, etc.) before entry into a focal industry increased the variety of options considered at entry.

However, once founders with diverse industry experience choose to enter a focal industry, the benefits of diverse industry experience turn into the severe liabilities. As they wandered through various industries before founding new ventures, founders with diverse industry experience did not have sufficient time to be experts in any given focal industry. In contrast, founders with domain-specific knowledge in one industry may benefit from greater tacit knowledge of the products, processes, and technologies used in a focal industry, and may be better at recognizing viable market opportunities in a focal industry and at predicting the future of new ventures. Eventually, founders with domain-specific knowledge are more likely to undertake market scope expansion, which requires a significant level of knowledge about products and their marketability.

Founders with diverse industry experience are cognitively unconstrained, and a have high level of cognitive flexibility, all of which allows them to be exposed to many possible opportunities. However, because they lack relevant knowledge about a focal industry, they do not have the capacity to materialize such opportunities, and are therefore less likely to expand their market scope.

Thus,

Hypothesis 2: New ventures with founders that have diverse industry experience will have narrower product market scope than those without.

Data and Methodology

Research Context: The Global Lithium-Ion Battery Cell Manufacturing Industry

The empirical setting for this study is the global lithium-ion battery (LIB) cell manufacturing industry during its period of emergence from 1991 to 2014. The LIB cell manufacturing industry initially emerged in 1991 with the development of the first commercial LIB by Sony

Corporation.[1] The industry experienced slow global growth until the mid-1990s due to the narrow market applications of LIB (i.e Consumer Electronics). The emergence of environmental concerns about greenhouse gas emissions and the subsequent increase in research funding, subsidies, and tax incentives from federal and state governments broadened the market applications of LIB into electric vehicle and energy storage and invigorated the industry since late 1990s. Figure 1 depicts the pattern of entry into the LIB industry. The number of entrants rapidly increased from around 1999, peaked in 2009, and declined gradually thereafter as a result of intense competition, the global financial crisis and weakening governmental support. The observed entry pattern shows that the industry has not yet experienced a major shake-out, with few exit events occurring during the studied period. Therefore, my analysis captures the early and growth phases of the industry (Agarwal and Gort 1996).

In addition to its economic and policy prominence, the LIB cell manufacturing industry represents an ideal setting through which to examine the drivers of new ventures' market choices and expansion paths in an emerging industry because of the product's clear-cut market applications and founders' heterogeneous pre-entry experience. The industry has 10 distinct LIB market applications: (1) consumer electronics, (2) military, (3) medical, (4) aerospace, (5) marine, (6) industrial, (7) UPS (Uninterruptible Power Supply), (8) RFID (Radio-Frequency Identification), (9) automotive, and (10) energy storage, thus allowing me to track the trajectories of new ventures' market scope paths over time since their founding. Compared to other high-tech industries, the pre-entry experience of entrants varies significantly. The founders of new ventures that entered the LIB industry came from a variety of backgrounds (Greentechmedia, 2014). For

[1] Compared to other types of commercial rechargeable batteries, LIB outperformed in terms of energy density, life cycle, and recharging speed.

instance, some came from the finance industry (i.e. venture capital, investment banking, and real estate), while others had been employed in the information technology or telecommunication industries. The remaining 60 percent of founders were employees of relevant industries such as energy, chemistry, and electrical engineering.

Industry Background

Although researchers at the University of Texas at Austin made crucial contributions to the development of the rechargeable lithium-ion battery in the 1980s, American firms at that time declined to enter the industry, leaving it to better established electronics companies in Japan. As a result, for years the United States had almost no presence in lithium-ion batteries. In the late 1990s, when Toyota raced ahead with its first hybrid vehicles, the United States belatedly learned the importance of acquiring relevant battery manufacturing capabilities. The American firms are now moving aggressively to catch up to the Asian giants by enhancing R&D capabilities at national labs and universities, and through federal and state funding. The reality, however, is that five Japanese and two Korean battery manufacturers are 10 years ahead in the high-volume production of lithium-ion batteries (Farley, 2010). Figure 2 confirms that Asia holds an overwhelming market share of LIB manufacturing, and only one company in the United States – A123Systems – appears near the top with a 1 percent world market share.

Data Sources

I studied the population of global LIB cell manufacturing ventures founded since the industry emerged in 1991. The data-gathering process began by refining research questions and hypotheses through interviews with representatives from 12 LIB manufacturing firms that attended the Advanced Automotive Batteries Conference held in Michigan in September 2014.

First, I identified all manufacturers in Thomson One, which lists all types of rechargeable battery cells (commonly classified by Standard Industrial Classification (SIC) code 3691 or 3692). Second, as it is not possible to distinguish between LIB and other types of rechargeable batteries (i.e. Lead-Acid and Nickel Cadmium Batteries) based on the two SIC codes above, I identified the LIB firms that were listed in major international industry conferences (i.e. International Battery Seminar), industry trade journals (e.g. Batterypoweronline), or periodicals from research institutes (e.g. Navigant). Finally, I used the Who Owns Whom directory to obtain information on the ownership structure of LIB firms. A total of 244 global LIB firms were eventually selected for the population.

I drew on several sources of data to construct variables and to determine the final sample. First, I subscribed to product-level data from the Shmuel de Lion market research institute and industry trade journals to generate the dependent variable: firms' yearly product market scope since founding. I supplemented this information through LIB firms' websites, as well as telephone and email correspondence, as Shmuel de Lion does not have complete information on the market scope of all 244 firms. From a total of 24,500 documents that I collected for this variable, I selected 2,034 documents from 103 LIB cell manufacturing firms which contained information on yearly market scope.

Second, I collected information on founders' career trajectories before founding new ventures in the LIB industry to create explanatory variables. Given that new ventures' knowledge originates from founders' prior industry experience, I tracked their pre-entry experience including relevant industry experience, diverse industry experience, and founding experience to examine the relationship between founder pre-entry experience and his/her new ventures' market scope choices. I researched each firm's founder through Bloomberg Businessweek, LinkedIn, and corporate websites. In addition, I subscribed to self-reported data sets from Corptech and Zoominfo to capture each founder's working trajectory. As a result, I was left with 89 LIB cell manufacturing firms out of 244 for this particular variable.

Third, I chose to use United States Patent and Trademark Office (USPTO) data to generate a control variable for new ventures' technology structure. The LIB industry is in a relatively early stage given that many ventures were founded in the 2000s, and the annual number of applied patents has risen sharply in recent years (Wagner et al, 2013). However, publicly available patent data was insufficient to track the recent patent activities of new ventures. Therefore, I subscribed to INNOVACCER's patent data set, which is updated on a monthly basis up to 2014. Through that process, 96 out of 244 firms were selected to measure LIB cell manufacturers' technological invention.

Finally, I collected data from VentureXpert, the Department of Energy, local newspapers, and industry trade journals to control for individual, organizational, and environmental variances. After merging the data set including dependent, independent, and control variables, the final sample included 84 global LIB cell manufacturing ventures and 944 observations during the sample period of 1991-2011.

A key advantage of this data is as follows: First, because my sample consists of all prospective new ventures within a single industry since its emergence, it avoids the survival bias that plagues many studies that explore entrepreneurial phenomena (Beckman and Burton, 2008). Second, it assesses objective factors via direct collection of founder working trajectories, rather than relying on respondents' subjective memories about their pre-founding experiences

(Dencker, Gruber and Shah, 2009; Gruber, 2010; Dencker and Gruber, 2015). Third, the influence of right censoring is minimized as I ended the study period in 2011 to allow sufficient time for the approval of patent applications that sample firms made during the period.

Taken together, the data allows me to track the entire history of founders' working trajectories and of new ventures' technology development paths, while also precisely tracking detailed market expansion paths. By merging data sets that are based on different theoretical underpinnings – entrepreneurship, technological management, and firm scope – my study uncovers how new ventures' strategic choices are influenced and determined by founder characteristics.

Measures

Dependent Variable. The dependent variable, *Market Scope*$_t$, is a count variable capturing the accumulated number of new LIB ventures' product market choices from their founding within LIB industry in year t. Ten distinct product market application sectors were identified: (1) consumer electronics, (2) military, (3) medical, (4) aerospace, (5) marine, (6) industrial, (7) UPS (Uninterruptible Power Supply), (8) RFID (Radio-Frequency Identification), (9) automotive, and (10) energy storage. I collected yearly information on market scope since founding from industry trade journals (i.e. BatteryPowerOnline), and LIB cell technological specification documents from Shmuel de Lion, Lexis-Nexis Academic press announcements, and firm websites.

Independent Variables.

Founder Relevant Industry Experience indicates whether founders had experience relevant to the LIB industry before they founded new LIB ventures (Brüderl et al., 1992; Gimeno et al., 1997). I collected each founder's detailed working trajectory through trade journals, LinkedIn, Bloomberg Businessweek, and Zoominfo, and by visiting firm websites. Based on a combination of SIC classification and interviews with six Chief Technology Officers of LIB firms at major industry conferences (i.e. The Battery Show), I categorized relevant vs non-relevant pre-industry experience. Founders' pre-industry experience in battery, energy, chemistry, and electrical engineering firms were categorized as relevant industry experience, and other experience was coded as non-relevant. I then created a binary variable whose value is 1 when founders have prior working experience relevant to the LIB industry, and 0 otherwise. For firms with multiple founders, I compiled relevant industry experience by accounting for all founders; thus, the firm with relevant pre-industry experience will be coded 1 if any one of its founders had experience in relevant industries.

Founder Founding Experience captures whether founders had pre-founding experience before starting new ventures in the LIB industry (Wright et al, 1997; McGrath and MacMillan 2000). After compiling background information through trade journals, LinkedIn, Bloomberg Businessweek and Zoominfo, and by visiting firm websites, I coded the variable as 1 if founders were founders of another firms previously, and 0 otherwise. For firms with multiple founders, I collected pre-founding experience of all founders. The firm with pre-founding experience will be coded as 1 if any of its founders was a serial entrepreneur.

Founder Diverse Industry Experience captures the degree to which founders' prior industry experience was gathered from a variety of industries. This variable was measured using a count variable that tallied the number of industries in which founders had prior work experience before they founded new ventures in the LIB industry (Fern et al, 2012). Using detailed information on founders' career trajectories, I calculated the sum of founders' industry experiences and coded a founder as 1 if they worked for at least two different industries, and 0 otherwise. There exists time lag between independent variables and dependent variable.

Control variables

I controlled for a number of individual, organizational, and environmental factors that might influence the market scope of new ventures (Dencker, Gruber, and Shah, 2009). At the individual level, I controlled for founder demography including *Gender, Educational Background,* and *Years of Prior Working Experience*, all of which may influence entrepreneurs' strategic choices (Kalleberg and Leicht, 1991; Dencker and Gruber, 2015). For these variables, I only considered the demographic information of the primary founder of each new venture. I coded *Gender* 1 if the founder was male and 0 if the founder was female. I measured *Educational Background* based on founders' final academic degree. I coded *Educational Background* 1 if the founder's final degree is a Ph.D., and 0 otherwise. I measured *Years of Prior Working Experience* by tracking each founder's working trajectory from various sources including Zoominfo, Bloomberg Business week and Linked-In[2].

I controlled for organizational-level factors with measures of *Technological Focus*$_{t-1}$, *Tech Breadth*$_{t-1}$, *Firm Size, Firm Age, Sole Founder Venture, Incumbent Backed Venture, Internalization, and VC Funding.* Prior literature posits that the manner through which new ventures develop their technological knowledge significantly affects the degree of market scope expansion (Silverman, 1999; Miller, 2004). I captured the knowledge structure of new ventures' technology portfolio based on two dimensions of technology breadth and focus using USPTO

[2] Two coefficients are high enough to cause concern, as the correlation between *Years of Prior Working Experience* and *Founder Age* exceeds 0.90. Due to such high correlation between the two, it may cause potential problem of multicollinearity that inflates the variance of the model. Thus, I omitted *Founder Age* in the statistical models.

data. *Technology Breadth* represents the number of knowledge components in a focal firm's patents (Fleming and Sorenson, 2001). The value of the variable is the total number of primary class patents in the firm in a given year, and the variable was measured for year t-1 when the dependent variable was measured for year t (Nesta, 2008). *Technological Focus* represents the focus of the firm's technological activities, measured using the Herfindahl index (Blau, 1977). I calculated the index using the following formula:

$$D = \sum {p^2}_i$$

where P_i stands for the share of patents in class i during the past year. The maximum value of 1 represents a firm that filed all of its patents in the same main patent class, whereas values approaching 0 represent a situation where every patent filed by the firm is in a distinct patent class of its own. For example, a value of 0.95 indicated a high level of technological focus, and a value of 0.05 indicated a high level of technological diversity. The variable was measured for year t-1 when the dependent variable was measured for year t.

Prior literature suggests that larger firms are less likely to be resource constrained, thus more likely to pursue broader types of strategic choices (Agarwal and Audretsch, 2001; Hariharan and Brush, 1999). I measure the size of the firm by using the number of employees. Firm size is often measured in revenues or market share; however, most samples are privately held companies and therefore do not publicize this information. Thus, measuring firm size through the number of employees provides a reasonable alternative (Shan *et al*., 1994). *Firm Size* was the natural logarithm of the total number of employees, including executives. I also include firm age in the models for two reasons. First, previous research has shown that models of size effects that fail to control for age yield biased estimates of the effects of size on organizational outcomes, due to the typically strong positive correlation between the two variables (Barron, West and Hannan 1994). Second, firm age also affects the tendency for firms to expand into other markets (Denis, Denis, and Sarin, 1997). *Firm Age* was simply calculated as a given year t minus founding year of the firm. Because new ventures with one sole founder might be fundamentally different from those with multiple founders, consistent with prior literature (Sine, Mitsuhashi, and Kirsch, 2006), I control for the former with the variable *Sole Founder Venture*, which is coded 1 if a firm had only one founder, and zero otherwise. In categorizing new ventures, incumbent-backed ventures are separate legal entities with formal ties to the incumbents (Agarwal et al, 2004), and represent a hybrid between start-up and diversifying entrants. I coded *Incumbent Backed Ventures* 1 if new ventures are joint venture or subsidiaries. Prior literature maintains that firms that are vertically integrated will lose economies of scale and be forced to manage more complex routines (Randall and Ulrich, 2001), thus affecting product market scope. I controlled for *Internalization* with an indicator variable that takes the value of 1 if the firm not only manufactures cells, but also packs and assembles cells into battery, and 0 if the firm only focuses on cell manufacturing activity. I collected information on boundary choices at founding from firms' websites and industry publications. I also ensured that these boundary choices remained unchanged, making sure there were no switches between internal and external modes within the sample firms. Previous literature also suggests that resource availability affects founders' decision making (Helfat and Lieberman, 2002). Because a founder with a resource slack should feel less pressure for speedy market expansion, thus spend more on diverse search to find ways of how to reconfigure their knowledge, access to financial resources will affect new ventures' search for market opportunities (Gruber, MacMillan, and Thompson, 2008). I utilized a dummy variable – *VC Funding* – to indicate whether new ventures acquired such seed funding. This variable has a value of 1 if the firm acquired seed funding, and 0 otherwise.

At the environmental level, I controlled for market scope of prior year by generating one-year time lagged variable – *Market Scope*$_{t-1}$. I also controlled for *Annual Industry Growth*$_{t-1}$. Research on industry evolution posits that firms' strategic decision making is influenced by the growth stage of their industry (Agarwal and Bayus, 2002; Carroll, Bigelow, Seidel, and Tsai. 1996). This variable was measured for year t when the dependent variable was measured for year t + 1. I also controlled for time period effects due to changes in policies and regulations related to the LIB industry using *Year Dummy* variables pertaining to the different years in which firms operated. The omitted category was 1991 – the first year of the study period. These variables allowed me to control for factors specific to a particular year that might affect firms' product market scope for that year. Lastly, since national economic situations and culture may affect new ventures' strategic decision making, I controlled for the country in which the firm was founded by creating a dummy variable – *US* – which I coded 1 if new ventures are located in the United States, and 0 otherwise.

Statistical Methods

My data structure is yearly panel data that is unbalanced, implying that the number of observations varies by firm, as some firms leave the sample earlier than others. The unit of analysis is the firm year, with 84 firms yielding 944 firm-year observations. I estimated models using firm random effects for four reasons: (1) the independent and some control variables are constant over time, (2) significant unobserved heterogeneity was present (Greene, 1997), (3) Hausman specification tests were not significant, and (4) significant serial correlation was not present.

The dependent variable – the number of market segments where the sample firms enter over time takes on only non-integer values. An ordinary linear regression is not applicable for this type of variable, as it relies on the normality of the dependent variable (Wooldridge, 2002). Poisson regression can be used to model count variables if the assumption of the equality of the conditional mean and variance functions is not violated (Greene 2003). DV does not show over-dispersion problem, I use a Poisson regression model for my study (Poisson is better model – Nandini can share the citation). I also used robust standard errors to correct for potential non-independence across observations.

Results

Table 1 presents a descriptive statistics and correlation matrix for the variables used in the analyses. The descriptive statistics illustrate that the samples are generally small firms with narrow market scope expansion paths. They also show that 66 percent of new ventures were started by founders with relevant industry experience (i.e. battery) and around 40 percent of them were founded by those with working experience from at least two different industries. Although there are many pairs of variables that show significant pairwise correlations, in general correlation between the variables is moderate. In addition, my models do not suffer from multicollinearity issues, as the variance inflation factor (VIF) for *Year Dummy* is the highest (3.02), which is below the recommended cutoff level of 10 (Neter, Kutner, Nachtsheim, & Wasseman, 1996).

Table 2 shows the results from a Poisson regression analysis of new venture market scope. Model 1 contains control variables only, and Model 2 adds *Founder Relevant Industry Experience* to test the main effect of founder relevant industry experience on new venture market scope. The coefficient of *Founder Relevant Industry Experience* is positive and significant ($p<0.01$), supporting Hypothesis 1A. In other words, if founders have relevant industry experience before founding new ventures in the LIB industry, they are more likely to expand market scope over time. Consistent with Hypothesis 1B, the coefficient of *Founder Founding Experience* is also positive and marginally significant ($p = 0.074$). Model 3 indicates that when founders have pre-founding experience before founding new ventures in the LIB industry, their new ventures are more likely to expand their market scope over time, a pattern that holds in Model 5. Turning to Hypothesis 1C, Model 5 suggests that founders with relevant industry experience are more likely to expand their new ventures' market scope than founders with founding experience. Using a post-estimation *test* command in STATA, I found that the difference between the coefficient for relevant industry experience and founding experience was significantly different from zero – consistent with Hypothesis 1C. In particular, this test command yielded an F statistic of 15.97, which was significantly different from zero ($p<0.01$). Model 4 tests Hypothesis 2 – the effect of founder diverse industry experience on new venture market scope. The coefficient of *Founder Diverse Industry Experience* is negative, and marginally significant ($p=0.085$), supporting Hypothesis 2.

Robustness Checks

A LIB cell composes of four major components: Cathode, Anode, Separator, and Electrolyte. Among these parts, technological choices in cathode materials differentiate LIB cell performance in terms of power and density (Wagner et al, 2013). In this sense, new ventures' market choices are mainly determined by the cathode materials they use to manufacture a LIB cell. For example, if firm A uses NMC cathode materials in cell manufacturing, we can expect its targeted market to be electric vehicles, whereas if firm B uses LCO cathode materials in cell manufacturing, we can expect its targeted market to be consumer electronics.

Figure 3 shows the historical trend of patenting activity for the five most commonly used cathode materials – LCO, spinel, NMC, olivine, and NCA. As the figure illustrates, each cathode's invention year is significantly different. For example, while LCO was invented in 1980, NMC, the newest cathode material, was invented in 1999. This means that all five cathodes were not available until 1999, implying that the number of available markets new ventures can enter before 1999 was narrower than after 1999. Given the difference in terms of total number of markets before and after 1999, I restricted my observation of new venture market scope trajectories after 1999 to control for this crucial difference in market environments. After excluding new ventures' market scope expansion paths before 1999, the total number of observations for 84 new ventures was 888.

Table 3 presents the results of robustness checks using Poisson models with restricted sample. As shown in Table 3, the results from the Poisson models provide support for all four hypotheses as the results shown in Table 2.

My analysis of the drivers of the market scope is contingent on firms that have to be chosen in the single industry firms at the time of the founding. Since my research question does not focus on the systematic differences between single industry vs mutliple industry entrants, rather focuses on the understanding of how industry experience within the single industry, I excluded diversify entrants (i.e. Sony).

Discussion

By employing a rich longitudinal data set within a high-tech industry from the point of its emergence, my research has begun to shed light on a key issue in entrepreneurship and strategy: the effect of founder characteristics on market scope paths after entry into a focal industry. My study extends prior research by showing that features of founder pre-entry experience exert a significant influence not only on market scope choices at entry, but also on market scope paths throughout the growth stage of new ventures. I developed several hypotheses that relate a founder's accumulated experience to one of the key strategic choices they need to make – how to set their venture's market scope. Specifically, I explore how different types of founder pre-entry experience affect the market scope paths of new ventures. I test this question using a unique data set that captures the full history of changes in market scope over time for a sample of 84 global lithium-ion battery cell manufacturing ventures from 1991 to 2014. I found that both relevant industry experience and prior founding experience fosters market scope expansion, whereas diverse industry experience constrains market scope expansion. Furthermore, the positive effect of relevant industry experience is more pronounced than the effect of prior founding experience.

Contributions and Implications

My findings reveal a number of key insights. First, this study has important implications for research on entrepreneurial decision making. So far, the extant research on entrepreneurship has focused on firms during their early years of operation and, thus, overlooks the critical role founder prior experience plays in forming the seed of a new venture's evolution and long-term prospects (Beckman, 2006, Shane, 2000; Shane and Khurana, 2003). To fill this gap, I explored the significant influence that founder pre-entry experience exerts on formulating the market scope trajectories of new ventures over time. Further, my study also contributes to entrepreneurship literature investigating how founders' knowledge endowment shapes new firm performance (Brüderl et al, 1992; Carroll and Mosakowski, 1987; Shane and Stuart, 2002; Unger et al., 2011). The major shortcoming of this stream of research is the inconclusive evidence regarding the role that a founder's knowledge plays in affecting new venture outcomes including survival (Brüderl et al, 1992), and sales (Delmar and Shane, 2006). One way to resolve this inconsistency is to consider the intermediate processes affected by founder characteristics which then influence new venture performance later on. By investigating one of the key strategic choices of new ventures – market scope – my study shows how different types of knowledge endowment foster/constrain the market scope expansion of new ventures. Although my study cannot directly answer the question of which product market scope strategies are more profitable, the unique assets derived from each type of founder experience may provide a clue. Founders who have relevant industry experience may be best positioned to choose more promising markets within a focal industry, as they have accumulated a tacit understanding of the industry's products, markets and resources.

My study also contributes to the burgeoning literature of intra-industry diversification (Stern and Henderson, 2004; Li and Greenwood, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013), defined as new ventures' presence in more than one product line (Stern and Henderson, 2004) or operation in more than one market (Li and Greenwood, 2004) within a single industry[3]. Given the prevalence of this phenomenon in high-tech industries (Tanriverdi and Lee, 2008), research has begun to investigate the link between intra-industry diversification and performance (Zahavi and Lavie, 2013). By claiming that intra- and inter-industry diversification are fundamentally different, this stream of research largely examines the performance implications of intra-industry diversification (Wu, 2013; Zahavi and Lavie, 2013). Still missing in this conversation, however, is theorizing on the antecedent of intra-industry diversification. Given that new ventures and established firms are inherently different entities, we need to separately scrutinize factors that affect the market scope of new ventures. To respond this call, recent studies have begun to look into how environmental factors affect the degree of market scope expansion within a single industry (Wu, 2013; Gambardella and Giarratana, 2013). However, by recognizing the fact that due to the lack of experiential knowledge within the focal industry new ventures' resources and capabilities mainly originate from founders, , my study complements the literature by shedding light on internal firm factors that affect market scope. By showing that founder knowledge endowment as a basis for firm-capabilities is related to the market scope of new ventures (Døving and Gooderham, 2008), my study proposes that founders have a paramount impact on the market scope choices of their new ventures.

Furthermore, my research provides important insights into evolutionary economics. Thus far, extant research on evolutionary economics has examined either how pre-entry experience shapes new ventures' initial strategies (Helfat and Lieberman, 2002; Helfat and Raubitschek, 2000) or it has delved into the relationship between pre-entry experience and firm performance

[3] Although the concept of firms' market scope, which is characterized by the range of customer segments firms are positioned to target, is subtly different from within-industry product diversity, defined as the degree of variation in a firm's portfolio of related products in a particular industry (Stern and Henderson, 2004) , I use them interchangeably in the study.

(Agarwal et al, 2004; Klepper, 2002; Wenting, 2008; Simons and Roberts, 2008, Chatterji, 2009). The literature therefore leaves the effect of pre-entry experience on post-entry strategies, including the evolution of market and technological choices, within a black box. By furthering inquiries into the effect of pre-entry experience on post-entry strategic choices, my study fills significant gaps in the study of evolutionary economics.

The study also provides several empirical contributions. First, it uses a yearly count of markets where new ventures enter, unlike many studies that either use a dichotomous variable capturing whether or not market scope change was made after founding, or rely on respondents' memories to provide self-reported data on market scope change. By collecting specific technological information on both products and the critical dimensions that founders consider when expanding their product market scope – the choice of cathode material – my study precisely captures changes in product markets over time.

Second, the study enriches literature on pre-entry experience by decomposing coarse firm-level data on pre-entry capabilities into the delicate details of founder-level prior experience (Qian et al, 2012; Kapoor and Furr, 2015). Research on industry evolution has largely measured pre-entry experience as a dichotomous, firm-level variable (i.e., diversifying entrants versus start-ups), even though the literature acknowledges the fact that start-ups may benefit from their founder's pre-entry experience (Agarwal et al.2004, Helfat and Lieberman 2002, Klepper 2002). By collecting the detailed career trajectories of founders, my study captures the rich heterogeneity in the types of experience new ventures bring into an emerging industry.

Limitations and Future Research

I am cognizant of the limitations of my study. First, my research is based on an industry that is approaching maturity but has not yet arrived at the shake-out stage. Ideally, an examination of my theoretical predictions through the entire life of an industry would make for a more complete story, thus increasing the power of generalizability. Replicating this study in other industries would be one promising venue for future research.

In addition, founder origin needs to be studied more specifically. Although I tracked founders' working trajectories before entry into the LIB industry, the operationalization of founder relevant industry experience can be detailed further. From the sample, relevant industry experience incorporates both experience from upstream industries (i.e. electrical engineering, chemical industries) and downstream industries (i.e. battery, energy industries). Given that the content and scope of the knowledge gleaned from upstream and downstream industry experiences is quite different, further studies could look into the distinctive impact of different types of founder relevant industry experience on the strategic decision making of new ventures.

Although random effects model was used to control for unobserved firm heterogeneity, my findings are still subject to unobserved heterogeneity. For example, unobserved factors such as behavioral and personality characteristics unique to different founders may play a role in their decisions to expand the product market scope of their new ventures. Incorporating founders' behavioral patterns, such as their degree of risk aversion and their personality into this vein of research would enrich the literature.

Although my findings indirectly answer the question of which product market scope strategies are more profitable, the study does not paint a whole picture incorporating the determinants and consequences of new venture market scope trajectories. Thus, it is still unclear whether and how founder knowledge endowment can enhance new ventures' survival likelihood through choices on market scope. My next study will unpack how the genesis of market scope choices can enhance/hamper the chances of firm survival. Through a rich data set in which I have collected detailed information on the exact time of market scope expansion events during the life cycle of new ventures, I can rule out the possibility of simultaneity in the relationship between market scope and new firm survival.

Tables and Figures

Table 1. Descriptive Statistics and Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Scope$_t$	1											
Relevant Industry Experience	0.05	1										
Founding Experience	0.00	-0.06	1									
Diverse Industry Experience	0.08	-0.13	0.30	1								
Gender	0.02	-0.06	-0.11	0.01	1							
Education Background	0.12	0.37	-0.12	-0.16	-0.04	1						
Years of Working Experience	0.06	0.04	0.13	0.24	0.08	-0.11	1					
Tech Breadth$_{t-1}$	0.00	0.03	-0.02	-0.02	0.03	-0.03	0.00	1				
Tech Focus$_{t-1}$	0.03	0.11	0.00	-0.03	0.02	0.07	-0.09	0.03	1			
Firm Size	0.03	0.01	-0.13	0.01	0.15	0.04	-0.13	0.15	-0.06	1		
Firm Age	0.32	-0.13	-0.07	-0.04	0.12	0.01	-0.14	0.32	0.10	0.63	1	
Sole Founder Venture	0.03	-0.18	-0.25	-0.10	0.06	-0.03	0.11	0.06	-0.03	0.25	0.08	1
Incumbent Backed Venture	0.08	0.19	-0.15	-0.11	0.09	-0.13	0.04	-0.03	0.01	-0.16	-0.18	0.10
Internalization	0.17	-0.19	-0.02	0.03	0.12	-0.17	0.04	0.10	0.01	0.38	0.21	0.20
VC Funding	0.03	0.09	0.02	0.01	-0.06	0.29	0.03	-0.04	0.17	-0.35	-0.20	-0.31
Annual Industry Growth$_{t-1}$	0.33	-0.06	-0.04	-0.02	0.10	0.02	-0.08	0.02	0.03	0.11	-0.02	0.04
US	0.00	-0.07	0.33	0.13	-0.18	-0.03	0.06	-0.05	0.24	-0.25	-0.04	-0.11

	(13)	(14)	(15)	(16)	(17)
Incumbent Backed Venture	1				
Internalization	0.00	1			
VC Funding	0.00	-0.07	1		
Annual Industry Growth$_{t-1}$	0.05	0.02	-0.06	1	
US	0.02	-0.02	0.24	-0.02	1

Table 2 Panel Poisson Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		H1a	H1b	H2	H1a, b & c	H1a &H2	H1b&H2	H1a, b & H2
Relevant Industry Experience		0.0953***			0.0978***	0.0937***		0.0964***
		(0.0272)			(0.0263)	(0.0274)		(0.0269)
Founding Experience			0.0458*		0.0509*		0.0572**	0.0619**
			(0.0257)		(0.0262)		(0.0267)	(0.0268)
Diverse Industry Experience				-0.0413*		-0.0386*	-0.0496**	-0.0476**
				(0.0240)		(0.0220)	(0.0219)	(0.0197)
Gender	-0.00563	0.00293	-0.00636	-0.000934	0.00218	0.00744	-0.00115	0.00737
	(0.0751)	(0.0660)	(0.0813)	(0.0693)	(0.0724)	(0.6084)	(0.0755)	(0.0670)
Education Background	-0.00540	-0.0504*	-0.00239	-0.0166	-0.0481*	-0.0602**	-0.0149	-0.0595**
	(0.0247)	(0.0297)	(0.0239)	(0.0238)	(0.0286)	(0.0291)	(0.0218)	(0.0276)
Yrs of Working Experience	-0.00195	-0.00227**	-0.00209*	-0.00155	-0.00244**	-0.00189*	-0.00165	-0.00202*
	(0.00120)	(0.00101)	(0.00118)	(0.00122)	(0.00103)	(0.00105)	(0.00119)	(0.00105)
Tech Breadth$_{t-1}$	0.00299**	0.00336**	0.00305***	0.00280**	0.00343**	0.00318**	0.00284**	0.00323**
	(0.00117)	(0.00139)	(0.00118)	(0.00125)	(0.00141)	(0.00138)	(0.00129)	(0.00142)
Tech Focus$_{t-1}$	-0.0487**	-0.0708***	-0.0458**	-0.0492**	-0.0682***	-0.0709***	-0.0458**	-0.0678***
	(0.0220)	(0.0222)	(0.0221)	(0.0224)	(0.0222)	(0.0227)	(0.0226)	(0.0228)
Firm Size	-0.00322	-0.00590	-0.00320	-0.00137	-0.00597	-0.00411	-0.000930	-0.00373
	(0.00723)	(0.00673)	(0.00709)	(0.00738)	(0.00650)	(0.00664)	(0.00734)	(0.00645)
Firm Age	0.00354	0.00664*	0.00359	0.00410	0.00678**	0.00710**	0.00427	0.00737**
	(0.00322)	(0.00344)	(0.00311)	(0.00319)	(0.00324)	(0.00338)	(0.00303)	(0.00316)

Sole Founder Venture	-0.00493	0.0190	0.00307	-0.00758	0.0289	0.01614	0.00187	0.0274
	(0.0296)	(0.0303)	(0.0276)	(0.0307)	(0.0304)	(0.0317)	(0.0290)	(0.0325)
Incumbent Backed Venture	-0.000322	-0.0150	0.00499	-0.00143	-0.00944	-0.01554	0.00494	-0.00897
	(0.0379)	(0.0383)	(0.0381)	(0.0385)	(0.0385)	(0.0381)	(0.0386)	(0.0380)
Internalization	0.0288	0.0440*	0.0256	0.0324	0.0410*	0.0471*	0.0289	0.0441*
	(0.0261)	(0.0255)	(0.0256)	(0.0279)	(0.0248)	(0.0269)	(0.0269)	(0.0257)
VC Funding	-0.0146	-0.000956	-0.0109	-0.0117	0.00345	0.00156	-0.00659	0.00739
	(0.0231)	(0.0231)	(0.0229)	(0.0231)	(0.0231)	(0.0229)	(0.0228)	(0.0230)
Market Scope$_{t-1}$	0.402***	0.401***	0.404***	0.400***	0.404***	0.400***	0.398***	0.401***
	(0.0160)	(0.0153)	(0.0157)	(0.0159)	(0.0150)	(0.0159)	(0.0151)	(0.0146)
US	0.0493*	0.0679***	0.0387	0.0619**	0.0566**	0.0619**	0.0792**	0.0680***
	(0.0253)	(0.0244)	(0.0253)	(0.0256)	(0.0239)	(0.0256)	(0.0240)	(0.0231)
Year Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.411***	-0.496***	-0.408***	-0.385***	-0.494***	-0.385***	-0.470***	-0.463***
	(0.0872)	(0.0817)	(0.0930)	(0.0810)	(0.0873)	(0.0810)	(0.0771)	(0.0816)
Observations	944	944	944	944	944	944	944	944
Number of Firms	84	84	84	84	84	84	84	84

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3 Panel Poisson Regression Results with Sample Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		H1a	H1b	H2	H1a,b & c	H1a &H2	H1b&H2	H1a, b & H2
Relevant Industry Experience		0.0970***			0.0993***	0.0955***		0.0980***
		(0.0274)			(0.0266)	(0.0277)		(0.0273)
Founding Experience			0.0415*		0.0467*		0.0529**	0.0578**
			(0.0246)		(0.0257)		(0.0259)	(0.0266)
Diverse Industry Experience				-0.0419*		-0.0393*	-0.0495**	-0.0477**
				(0.0235)		(0.0213)	(0.0219)	(0.0194)
Gender	-0.00367	0.00477	-0.00450	0.00123	0.00390	0.00952	0.000832	0.00925
	(0.0749)	(0.0657)	(0.0805)	(0.0691)	(0.0716)	(0.0605)	(0.0747)	(0.0662)
Education Background	-0.00390	-0.0496*	-0.000699	-0.0154	-0.0470	-0.0598**	-0.0132	-0.0585**
	(0.0248)	(0.0299)	(0.0240)	(0.0238)	(0.0288)	(0.0295)	(0.0219)	(0.0279)
Yrs of Working Experience	-0.00209*	-0.00239**	-0.00219*	-0.00168	-0.00252**	-0.00202*	-0.00174	-0.00210*
	(0.00122)	(0.00103)	(0.00120)	(0.00125)	(0.00104)	(0.00108)	(0.00121)	(0.00107)
Tech Breadth$_{t-1}$	0.00291**	0.00335**	0.00296**	0.00270**	0.00341**	0.00316**	0.00273**	0.00319**
	(0.00116)	(0.00138)	(0.00117)	(0.00125)	(0.00140)	(0.00137)	(0.00128)	(0.00141)
Tech Focus$_{t-1}$	-0.0524**	-0.0748***	-0.0498**	-0.0531**	-0.0724***	-0.0751***	-0.0501**	-0.0724***
	(0.0229)	(0.0234)	(0.0229)	(0.0234)	(0.0233)	(0.0241)	(0.0235)	(0.0241)
Firm Size	-0.00273	-0.00582	-0.00268	-0.000712	-0.00585	-0.00386	-0.000240	-0.00345
	(0.00736)	(0.00687)	(0.00724)	(0.00750)	(0.00667)	(0.00678)	(0.00750)	(0.00664)
Firm Age	0.00344	0.00672*	0.00351	0.00394	0.00687**	0.00713**	0.00412	0.00740**
	(0.00324)	(0.00344)	(0.00313)	(0.00323)	(0.00326)	(0.00340)	(0.00307)	(0.00319)

Sole Founder Venture	-0.00260	0.0214	0.00463	-0.00478	0.0304	0.0190	0.00404	0.0296
	(0.0296)	(0.0304)	(0.0282)	(0.0307)	(0.0310)	(0.0319)	(0.0296)	(0.0330)
Incumbent Backed Venture	-0.00118	-0.0149	0.00391	-0.00280	-0.00946	-0.0160	0.00337	-0.00950
	(0.0384)	(0.0384)	(0.0386)	(0.0391)	(0.0386)	(0.0384)	(0.0392)	(0.0382)
Internalization	0.0297	0.0439*	0.0270	0.0329	0.0414*	0.0469*	0.0300	0.0443*
	(0.0266)	(0.0258)	(0.0261)	(0.0282)	(0.0251)	(0.0271)	(0.0271)	(0.0259)
VC Funding	-0.0181	-0.00294	-0.0146	-0.0155	0.00131	-0.000669	-0.0106	0.00494
	(0.0232)	(0.0232)	(0.0230)	(0.0231)	(0.0232)	(0.0230)	(0.0229)	(0.0231)
Market Scope$_{t-1}$	0.401***	0.400***	0.403***	0.399***	0.403***	0.398***	0.401***	0.400***
	(0.0161)	(0.0153)	(0.0158)	(0.0159)	(0.0151)	(0.0151)	(0.0154)	(0.0147)
US	0.0511**	0.0700***	0.0419	0.0635**	0.0601**	0.0813***	0.0539**	0.0714***
	(0.0255)	(0.0243)	(0.0257)	(0.0260)	(0.0240)	(0.0242)	(0.0256)	(0.0233)
Year Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.343***	-0.402***	-0.355***	-0.341***	-0.417***	-0.399***	-0.356***	-0.417***
	(0.0912)	(0.0869)	(0.0937)	(0.0855)	(0.0906)	(0.0818)	(0.0884)	(0.0859)
Observations	888	888	888	888	888	888	888	888
Number of Firms	84	84	84	84	84	84	84	84

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Entrants per Year and Total No. of Firm per Year in the Global LIB Industry

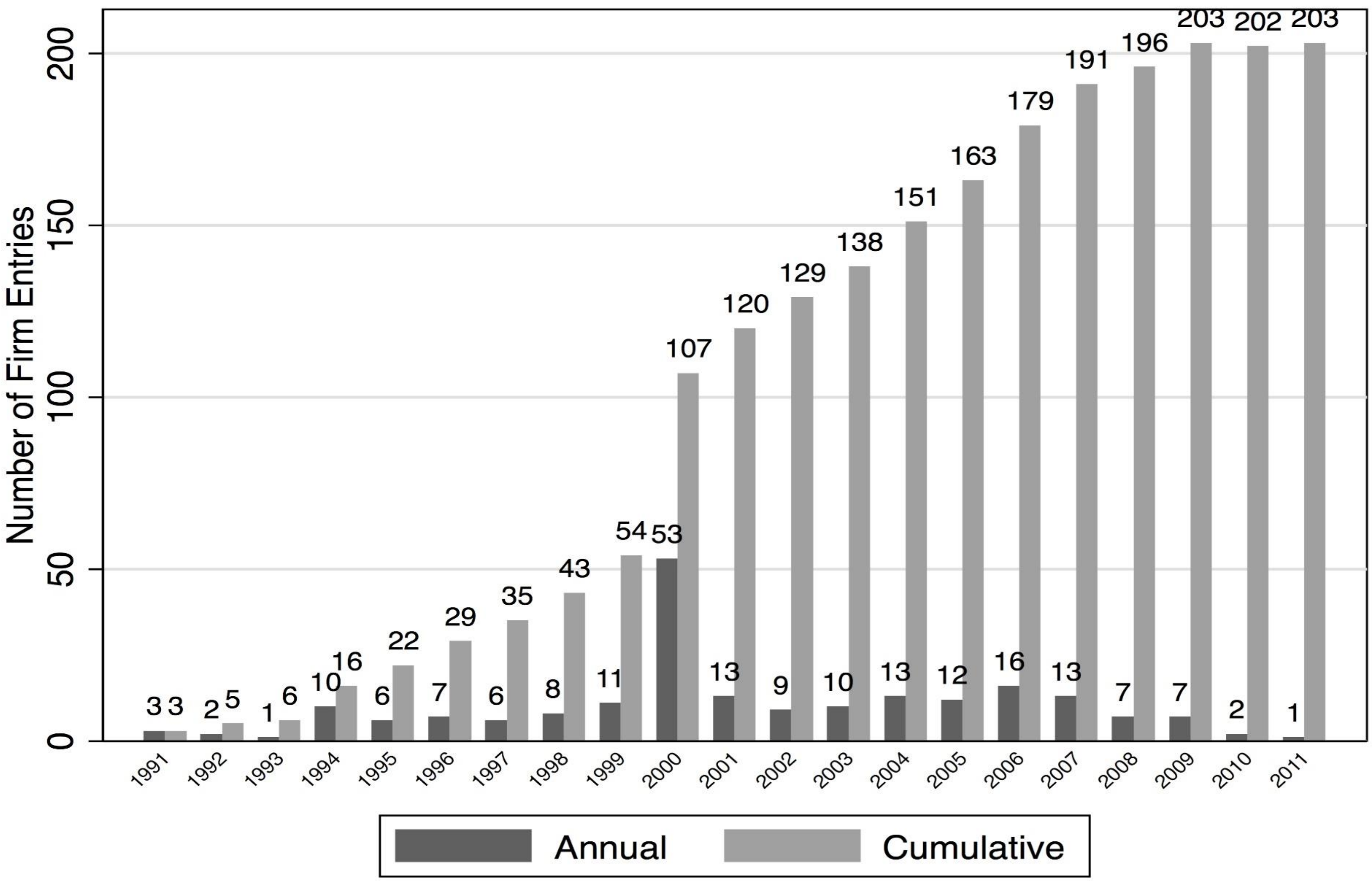
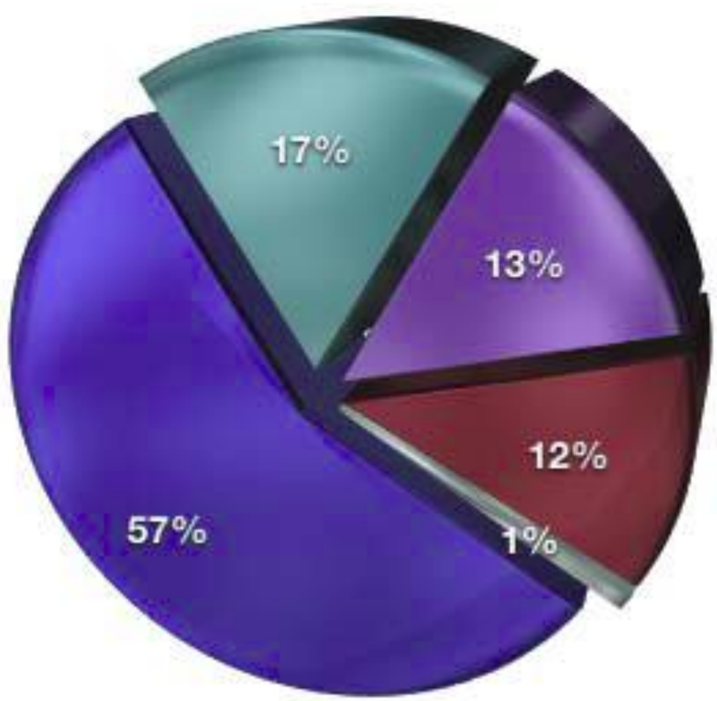
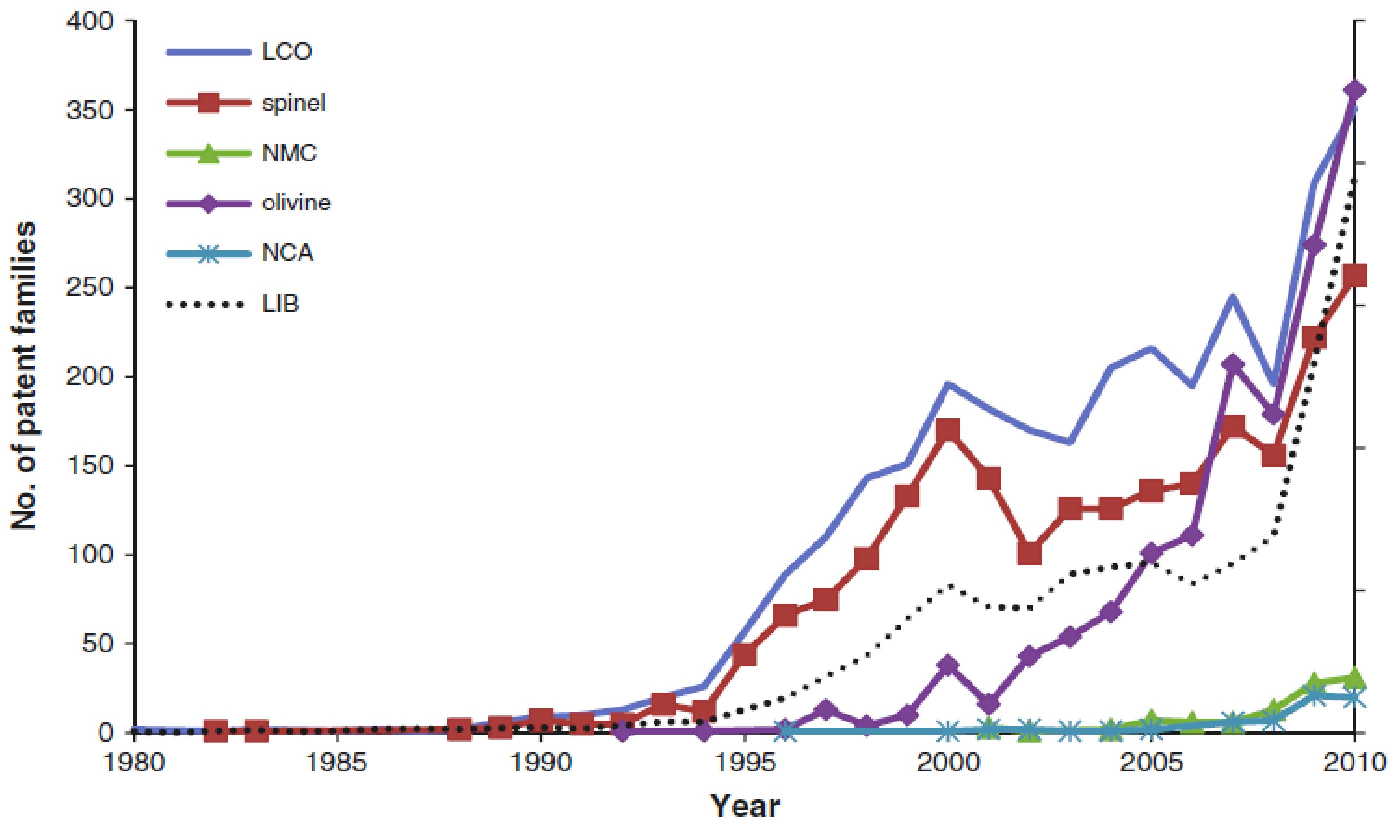


Figure 2. Global lithium-ion Battery Market Share, by Country and by Firm. Source Center on Globalization, Governance & Competitiveness Based on (METI, 2010; NEDO, 2009)



1. Sanyo (Japan)	23%
2. Samsung (Korea)	15%
3. Sony (Japan)	14%
4. BYD (China)	8.3%
5. LG Chem (Korea)	7.4%
6. BAK (China)	6.6%
7. Panasonic (Japan)	6.0%
8. Hitachi Maxell (Japan)	5.3%
9. ATL (China)	3.8%
14. A123 Systems (U.S.)	**1%**

Figure 3. Historical Trend of Patent Activity for the Various Positive Electrode Materials, as Measured by the Annual Number of Patent Families. Source PatBase, July 2012



CHAPTER 3: ESSAY TWO

THE EFFECT OF FOUNDER PRIOR EXPERIENCE ON SEARCH PATTERN OF NEW VENTURES IN THE GLOBAL LITHIUM-ION BATTERY INDUSTRY

ABSTRACT

While new ventures' search strategies play a crucial role in their innovative performance, little is known about why firms differ in the way they search for innovation. Drawing on technological search and entrepreneurship literature, my study fills this gap by examining how the various features of founder experience before entry into the focal industry determine two types of new ventures' search strategies – breadth and depth – in the global Lithium-Ion Battery (LIB) cell manufacturing industry from 1991-2014. Findings indicate that new ventures with founders whose prior industry experience is 'relevant' to a focal industry are positively related to both breadth and depth search strategies, whereas new ventures with founders whose prior industry experience is 'diverse' are negatively related to both breadth and depth search strategies.

Keywords: Search Strategies, Founder Prior Experiences, New Ventures' Strategic Decision Making, and Emerging Industries.

Introduction

Setting a firm's search strategy is one of the most fundamental organizational decisions since, through unique combinations of technological knowledge (Nelson and Winter, 1982), firms can improve their ability to innovate (Katila, 2002; Katila and Ahuja, 2002),and acquire future capabilities (Cohen and Levinthal, 1990), thus enhancing the chance of survival (Tushman and Anderson, 1986). However, the way firms search for technological knowledge are considerably different from each other. While some develop new knowledge by building on their existing technological domains (Stuart and Podolny, 1996; Katlia and Ahuja, 2002), others combine knowledge across broad technological domains (Rosenkopf and Nerkar, 2001; Katila, 2002). Considering the costs and benefits of each strategy (Ahuja and Lampert, 2001; Laursen and Salter, 2006; Lee, Park, Yoon and Park, 2010), firm heterogeneity in the loci of search suggests that there is no one search strategy that is optimal for generating a new knowledge.

Choices about search strategy are also of vital strategic importance for new ventures. Because knowledge is not stored in their memories due to the lack of experience at the time of entry to a new industry/market, such strategic decisions shape the organizational knowledge base through which they determine their technological path, especially in technologically intensive industries. For example, new ventures with repeated usage of a few knowledge elements will have deep understanding of a specific technological area, and thus may tend to pursue incremental innovation. On the other hand, new ventures that combine various new elements across technological domains will be exposed to diverse types of knowledge, and therefore may tend to seek radical innovation.

Given the significance of search strategies for new ventures' innovative performance, it is of theoretical importance to understand the factors that determine why firms make different search choices. Researchers have taken various approaches to uncovering the factors that influence how firms choose their search strategies. While market-based explanations stress the importance of external factors, including demand conditions and customer concerns (Schmookler, 1962; Christensen and Bower 1996; Ruttan, 1997), context-based explanations emphasize organizational factors, including both organizational (Argyres and Silverman, 2004; Toh, 2007), and knowledge structures (Yayavaram and Ahuja, 2008). Although these approaches help develop an understanding of the antecedents of firms' different search strategies, both explanations are insufficient and less applicable in the context of new ventures, where new technological knowledge is often combined under highly uncertain market demand (Freeman and Soete, 1997) as well as structural features are not yet firmly established. Given that a firm's search behavior is shaped by prior experience and current needs, along with the fact that new ventures lack experiential knowledge within the focal industry, founders' past experiences lead new ventures to select specific technological domains familiar to the founders (March, 1981), thus guiding their ventures' overall search pattern (Shane, 2000). In this sense, it is clear that we need to consider types of founder prior experience as another key driver for new ventures' search strategy choices.

Drawing on technological search and entrepreneurship literature, this study advances theories on the antecedents of search strategies in the context of new ventures by investigating how different types of founder prior experience exert an influence on the way new ventures conduct their searches. Building on past literature, I consider two dimensions of search strategies: search breadth and search depth (Katlia and Ahuja, 2002; Laursen and Salter, 2006).

Search breadth describes how widely a firm explores new knowledge, while search depth describes how deeply a firm reuses its existing knowledge (Katila and Ahuja, 2002), the former being associated with exploration and the latter with exploitation. In addition, I explore two forms of experience that founders can gain before entering into an emerging industry: relevant and diverse industry experience. While relevant industry experience is defined as prior experience gained from industries that are closely related to the focal industry (Helfat and Lieberman, 2002), diverse industry experience captures whether founders worked for a variety of industries before entry into the focal industry (Gruber, 2010).

The central argument of the paper is that while founders with prior working experience in industries 'relevant' to a focal industry are positively related to both breadth and depth search strategies, founders with prior working experience in 'diverse' industries are negatively related to both breadth and depth search strategies. I tested these hypotheses using a unique longitudinal data set – the entire population of global Lithium-Ion Battery (LIB) cell manufacturing ventures founded since the industry emerged in 1991. Because my sample consists of all prospective new ventures within a single industry over the 15-year period since its emergence, it avoids the survival bias that plagues many studies exploring entrepreneurial phenomena (Beckman and Burton, 2008). My empirical approach assesses objective factors via direct collection of founder working trajectories, rather than relying on respondents' subjective memories about their pre-founding experiences (Dencker, Gruber and Shah, 2009; Gruber, 2010; Dencker and Gruber, 2015). In addition, I used USPTO data to create the types of new ventures' search strategies, as USPTO has been commonly employed to understand the technical search process (Almeida and Kogut, 1999; Argyres and Silverman, 2004).

My study contributes to the literature in several ways. First, the study advances organizational search research that has paid little attention to theorizing on the antecedents of firms' search behavior (Terjesen and Patel, 2015) in the context of new ventures by introducing founders' prior experience as a key driver. Second, the study extends entrepreneurship research that has examined the effect of founder knowledge endowments on new venture performance (Brüderl, Preisendörfer, and Ziegler, 1992; Carroll and Mosakowski, 1987; Shane and Stuart, 2002; Unger, Rauch, Frese, and Rosenbusch, 2011) by delineating the intermediate process of how a founder's experience leads new ventures to select search strategies after entering a new industry. My research also fills significant gaps in evolutionary economics by examining the effect of pre-entry experience on post-entry strategies (Eggers, 2012).

Theory and Hypotheses

Building on technology strategy (Fleming and Waguespack, 2007; Rosenkopf and Nerkar, 2001; Nerkar and Paruchuri, 2005; Katila, 2002; Ahuja and Katila, 2001) and evolutionary economics (Nelson and Winter, 1982), this study models innovation as a combination of preexisting knowledge employing the metaphor of search (Nelson and Winter, 1982). These combinations are a result of a recombinant process in which firms discover possible combinations by searching through various pieces of knowledge in many different technological domains (Rosenkopf and Nerkar, 2001; Fleming and Sorenson, 2001).

Drawing on the work of Winter (1984), search strategy refers to an "organization's problem-solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja, 2002:1184). Among various dimensions on which firms differ in their technological search (Rosenkopf and Nerkar, 2001; Ahuja and Katila, 2004; Nerkar, 2003), I classified search strategies across two technological dimensions – search breadth and depth (Laursen and Salter, 2006). It is important to first find the theoretical frameworks through which I conceptualize search breadth and depth, since theories on the ease or difficulty with which a firm can pursue both searches, as well as empirical studies examining their impact on firm innovation, both crucially depend on whether the two search strategies are considered to be incompatible or co-existent. Although March's (1991) "continuum" view – the idea that interplay between the two ends up in a zero-sum game where breadth and depth searches compete for limited and finite resources – is generally accepted, some resources, such as knowledge, may be infinite (Shapiro and Varian, 1998). Moreover, access to external resources considerably reduces the constraint imposed on new ventures by the scarcity of internal resources. Considering the fact that resources often do not suffer from the constraint of scarcity, this study follows Katila and Ahuja's (2002) "orthogonal" view, implying that the two strategies can co-exist and the interaction between the two may have a positive impact on firm innovation. Taking an orthogonal view, search breadth describes how widely a new venture explores new knowledge, while search depth describes how deeply a new venture reuses its existing knowledge (Katila and Ahuja, 2002), the former being associated with exploration and the latter with exploitation.

Given the empirical findings that even firms within the same industry tend to follow different search strategies (Benner and Tushman, 2002; Laursen, Leone, and Torrisi, 2010; Phelps, 2010), it is evident that each has its advantages and disadvantages. Although depth searches do not allow for recombination of more distant knowledge, the costs related to a depth search are much lower (Tripsas and Gavetti, 2000). In addition, with a depth search, firms are better equipped to innovate in a reliable way by avoiding knowledge that did not work in the past (Fleming and Sorenson, 2004). Despite its reliability and relatively low costs, however, depth searches can often restrict firms' cognitive abilities, leading to myopic behavior (March, 1991; Levinthal and March, 1993). As a result, potential solutions from more distant knowledge domains are not even considered. To avoid this depth search trap, conducting a broader search beyond a firm's current knowledge base is also required for firm success (Gibson and Birkinshaw, 2004; He and Wong, 2004). Although scholars agree that both search strategies are needed for firm innovation, there is considerably less clarity on where each type of search originates (Gupta, Smith and Shalley, 2006).

Although the external environment shapes firms' search strategies to some extent, (Schmookler, 1962; Christensen and Bower 1996; Klevorick, Levin, Nelson and Winter, 1995), the variety of search strategies that can be seen even within the same industry implies that the search strategies may originate from inside the firm, that is, they relate to different managerial choices about how best to organize the search for innovation. Given the vast array of possible combinations of existing knowledge, (Fleming and Sorenson, 2001; Fleming and Sorenson 2004), and the fact that technological search is an extremely uncertain process where both feasibility and future uses are unknown (Nelson and Winter, 1982; Freeman and Soete, 1997), firms tend to conduct the search in a bounded rational manner, ensuring that each firm does not search in the same technological domains to acquire new knowledge (Cyert and March, 1963). Rather, the way firms set their search strategies is different based on their previous experience. New ventures, however, do not possess accumulated knowledge about technologies, products, and markets, and therefore their search strategies rely to a great extent on the past experiences of their founders. More specifically, a founder's past experiences lead them to select the specific technological domains he/she has paid attention to (March, 1981), thus guiding their ventures' overall search patterns (Shane, 2000).

One type of prior knowledge that has been of considerable interest to entrepreneurship scholars is founder pre-entry experience (Delmar and Shane, 2006; Qian, Agarwal, and Hoetker, 2012). In this study, I introduce two features of founder pre-entry experience examined extensively in entrepreneurship literature – 'relevant' and 'diverse' industry experience. Relevant industry experience is defined as prior experience gained in related industries before entry into a focal industry (Helfat and Lieberman, 2002). For example, if founders have working experience in the chemicals industry before entry into the LIB industry, I categorize that experience as relevant, as battery manufacture directly involves knowledge of chemicals. This implies that both the LIB industry and chemicals industry are closely related. In contrast, diverse industry experience captures whether founders worked for a variety of industries before entry into a focal industry (Gruber, 2010). For instance, if founders have broad work experience across the retail, manufacturing, and service industries before entry into the LIB industry, I consider this founder's industry experience to be diverse.

Founder Pre-entry Experience and Breadth Search Strategy

Founder 'relevant' industry experience and 'breadth' search

If founders enter a focal industry that is relevant to their past industry experience, they can enjoy several benefits that those lacking this type of experience cannot. First, rich knowledge about the focal industry context provides founders with advantages when trying to understand both relevant content as well as the underlying links between knowledge components. This benefit helps them perceive cues that the industry environments and technologies may be shifting

(Ericsson, 2006). Second, relevant founder experience provides a tacit understanding of the products, processes, and technologies used in a focal industry; the industry's leading suppliers and distributors; and the industry's competitive landscape (Cooper, Gimeno-Gascon, and Woo, 1994; Helfat and Lieberman, 2002). By recognizing potential new market opportunities in the industry more easily than those without such experience, founders with relevant experience are more capable of conducting broad searches. Looking at the empirical context, given that each market within the LIB industry requires significantly different technological components and that the level of competition varies greatly between market segments (Wagner, Preschitschek, Passerini, Leker, and Winter, 2013), founders with relevant industry experience possess tacit knowledge of the industry's technology and market opportunities, and are therefore more capable of broadening their search into various technological areas. Thus,

Hypothesis 1a: New ventures with founders with technology related industry experience will search more broadly than those without.

Founder 'diverse' industry experience and 'breadth' search

Diverse industry experience may be beneficial for new ventures in broadening their search boundaries because a founder with various industry experiences may bring different bodies of knowledge to the table when founding new ventures (Carlile, 2002). However, diverse industry experience may also become a severe liability if the costs of diverse experience outweigh its benefits. Moreover, this potential liability looks more pronounced in industries that are high-tech, characterized by a high level of uncertainty and turbulence.

Indeed, as they wandered through various industries before founding new ventures, founders with diverse industry experience may not have gained enough expertise in any given focal industry and they may not possess the high level of shared knowledge (Buckley and Carter, 2004). This leads their new venture to suffer from uncoordinated actions (Hambrick, Cho, and Chen, 1996). In addition, not only are they unable to accumulate tacit knowledge of the technologies, products, and processes needed in a focal industry, founders with diverse industry experience may also have a hard time recognizing viable market opportunities or predicting the future of markets in a focal industry. In sum, due to a lack of tacit knowledge about products and their marketability, they will be hesitant to explore their technological boundaries by expanding their knowledge base. Thus,

Hypothesis 1b: New ventures with founders with diverse industry experience will search less broadly than those without.

Founder Pre-entry Experience and Depth Search Strategy

Founder 'relevant' industry experience and 'depth' search

Literature on cognitive constraint has examined how founder relevant industry experience affects the strategic choices of new ventures (Ericsson and Charness, 1994; Edmondson, Bohmer, and Pisano, 2001). The literature emphasizes the tendency for founders with relevant experience to be cognitively inert while implementing the strategic choices of new ventures (Tripsas and Gavetti, 2000). The main argument is that the more founders' knowledge is formulated on the basis of relevant industry experience, the more their decision-making processes are cognitively bound by that experience. As a result, founders tend to only delimit possible strategic options which are contiguous to their relevant industry experience in the past. Applying this argument to new ventures' search strategy choices, as founders' knowledge accessibility is narrowly constrained by their relevant experience, search processes are also located closely around founders' current knowledge base, and founders will more likely to rely on the usage of specialized knowledge .

Thus,

Hypothesis 2a: New ventures with founders with technology related industry experience will search more deeply than those without.

Founder 'diverse' industry experience and 'depth' search

In contrast to the cognitive constraint argument above, literature on cognitive flexibility posits that if knowledge is obtained from diverse industry experience, such experience not only allows founders to be more cognitively unconstrained, it also provides founders with divergent perspectives (Eggers and Kaplan, 2009). Thus, when new ventures face strategic choices of setting their search strategy, diverse industry experience enables founders to come up with a wide variety of possibilities. However, while founders with diverse industry experience may have novel and different perspectives, thus enabling them to consider a number of options when their new ventures face strategic decisions, they tend to lack specialized knowledge about a focal industry, and therefore they do not have the capacity to materialize these options with any depth.

Thus,

Hypothesis 2b: New ventures with founders with diverse industry experience will search less deeply than those without.

Data and Methodology

Research Context: The Global Lithium-Ion Battery Cell Manufacturing Industry

The empirical setting for this study is the global Lithium-Ion Battery (LIB) cell manufacturing industry in the period 1991 to 2011. The LIB cell manufacturing industry initially emerged in 1991 with the development of the first commercial LIB by Sony Corporation. Figure 4 depicts the pattern of entry into the LIB industry. The number of entrants rapidly increased from around 1999, peaked in 2009, and declined gradually thereafter as a result of intense competition, the global financial crisis and weakening governmental support. The observed entry pattern shows that the industry has not yet experienced a major shake-out, with few exit events occurring during the studied period. Thus, my analysis captures the early and growth phases of the industry life cycle.

The LIB cell manufacturing industry represents an ideal setting through which to examine the drivers of new ventures' search strategy in an emerging industry for several reasons. First, the high research and development (R&D) intensity of the LIB industry implies that technology search is of considerable importance (Wagner et al, 2013). Second, the industry is also characterized by incessant technology change, which allowed us to examine the changes in a firm's knowledge base in an industry that has witnessed considerable technological change (Mueller, Sandner, and Welpe, 2015). Third, given the proclivity of new ventures to patent their inventions in LIB industry (Wagner et al, 2013), patents are major way to protect their technologies. Lastly, compared to other high-tech industries, the pre-entry experience of entrants varies significantly. The founders of new ventures that entered the LIB industry came from a variety of backgrounds (Greentechmedia, 2014). For instance, some came from the finance industry (i.e. venture capital, investment banking, and real estate), while others had been employed in the information technology or telecommunication industries. The remaining 60 percent of founders were employees of relevant industries such as energy, chemistry, and electrical engineering.

Data Sources

I studied the population of global LIB cell manufacturing ventures founded between 1991 and 2010, including firms that exited (either by failure or acquisition). The data-gathering process began by refining research questions and hypotheses through interviews with representatives from 12 LIB manufacturing firms that attended the Advanced Automotive Batteries Conference held in Michigan in September 2014. First, I identified all manufacturers in Thomson One, which lists all types of rechargeable battery cells (commonly classified by Standard Industrial Classification (SIC) code 3691 or 3692). Second, I excluded the diversifying entrants whose founding years were prior to 1991, as it is possible that firms which enter the LIB industry via other industries are better able to search better and effectively than *de novo* entrants. Third, as it is not possible to distinguish between LIB and other types of rechargeable batteries (i.e. Lead-Acid and Nickel Cadmium Batteries) based on the two SIC codes above, I identified the LIB firms that were listed in major international industry conferences (i.e. International Battery Seminar), industry trade journals (e.g. Batterypoweronline), or periodicals from research institutes (e.g. Navigant). Finally, I used the Who Owns Whom directory to obtain information on the ownership structure of LIB firms. A total of 244 global LIB firms were eventually selected for the population.

I drew on several sources of data to construct variables and to determine the final sample. First, I collected information on founders' career trajectories before founding new ventures in the LIB industry to create explanatory variables. Given that new ventures' knowledge originates from founders' prior industry experience, I tracked their pre-entry experience including relevant industry experience and diverse industry experience to examine the relationship between founder pre-entry experience and his/her new ventures' search strategy. I researched each firm's founder through Bloomberg Businessweek, LinkedIn, and corporate websites. In addition, I subscribed to self-reported data sets from Corptech and Zoominfo to capture each founder's working trajectory. As a supplement, I hired Chinese research assistants to obtain necessary information regarding Chinese firms, which lack data accessibility. As a result, I was left with 95 LIB cell manufacturing firms out of 244 for this particular variable.

Third, I chose to use United States Patent and Trademark Office (USPTO) data to generate a control variable for new ventures' technology structure. The LIB industry is in a relatively early stage given that many ventures were founded in the 2000s, and the annual number of applied patents has risen sharply in recent years (Wagner et al, 2013) (See Figure 5). Through that process, 96 out of 244 firms were selected to measure LIB cell manufacturers' technological invention.

Finally, I collected data from VentureXpert, the Department of Energy, local newspapers, and industry trade journals to control for individual, organizational, and environmental variances. After merging the data set including dependent, independent, and control variables, the final sample included 88 global LIB cell manufacturing ventures and 1068 observations during the sample period. A key advantage of this data set is that it allows me to track the entire history of founders' working trajectories and their ventures' search strategy. By merging data sets that are based on different theoretical underpinnings – entrepreneurship, search behavior, and knowledge – my study uncovers how new ventures' search strategies are influenced and determined by founder characteristics.

Measures

Dependent Variable: *Search Breadth* represents the number of technological areas where a focal firm has been engaged (Fleming and Sorenson, 2001). The value of this variable is the total number of primary technological classes that a focal firm accumulated during the past 5 years (Nesta, 2008). *Search Depth* represents the extent to which firms draw intensively from specific technological areas, measured using the Herfindahl index (Blau, 1977). I calculated the index using the following formula:

$$D=1-\sum p^2_i$$

where P_i stands for the share of patents in class i during the past 3 years. A 3-year moving window may capture a LIB firm's search behavior more accurately, since firms in the sample are new ventures that do not receive many patents per year, if any (Rothaermel and Deeds, 2004). The minimum value of 0 represents the exclusive usage of one specific technological area in developing new products, whereas values approaching 1 represent a situation where every patent filed by a focal firm is in a distinct patent class of its own. For example, a value of 0.05 indicates a high level of search depth, and a value of 0.95 indicates a low level of search depth.

Independent Variables

Founder Relevant Industry Experience indicates whether founders had experience relevant to the LIB industry before they founded new LIB ventures (Brüderl et al., 1992; Gimeno et al., 1997). Based on a combination of SIC classification and interviews with six Chief Technology Officers of LIB firms at major industry conferences (i.e. The Battery Show), I categorized relevant vs non-relevant pre-industry experience. Through this process, I concluded that pre-industry experience in battery, energy, chemistry, and electrical engineering firms would be categorized as relevant industry experience, with other experience coded as non-relevant. I then created a binary variable whose value is 1 when founders have prior working experience relevant to the LIB industry, and 0 otherwise. For firms with multiple founders, I compiled relevant industry experience by accounting for all founders; thus, a new venture can have relevant pre-industry experience if any one of its founders had experience in relevant industries.

Founder Diverse Industry Experience captures the degree to which founders' prior industry experience was gathered from a variety of industries. This variable was measured using a count variable that tallied the number of industries in which founders had prior work experience before they founded new ventures in the LIB industry (Fern et al, 2012). I calculated the sum of founders' industry experiences and coded a founder as 1 if they worked for at least two different industries, and 0 otherwise. Likewise, for firms with multiple founders, a new venture can have diverse industry experience if any one of its founders had experience in more than two industries.

Control Variables

I controlled for individual, organizational, and environmental factors that might influence new ventures' search strategies (Laursen and Salter, 2006). At the individual level, I controlled for founder demography, including *Gender* and *Years of Prior Working Experience*, both of which may influence entrepreneurs' strategic choices (Kalleberg and Leicht, 1991; Dencker and Gruber, 2015). For these variables, I only considered the demographic information of the primary founder of each new venture. I coded *Gender* 1 if the founder was male and 0 if the founder was female. I measured *Years of Prior Working Experience* by tracking each founder's working trajectory from various sources including Zoominfo, Bloomberg Business week and Linked-in[4].

I controlled for organizational-level factors with measures of *Firm Size, Firm Age, Sole Founder Venture, Incumbent Backed Venture, VC Funding,* and *Internalization*. Prior literature suggests that larger firms are less likely to be resource constrained, thus more likely to pursue broader types of strategic choices (Agarwal and Audretsch, 2001; Hariharan and Brush, 1999). I measure the size of the firm by using the number of employees. Firm size is often measured in revenues or market share; however, most samples are privately held companies and therefore do not publicize this information. Thus, measuring firm size through the number of employees provides a reasonable alternative (Shan, Walker, and Kogut, 1994). *Firm Size* was the natural logarithm of the total number of employees, including executives. I also include *Firm age* in the models since previous research has shown that models of size effects that fail to control for age yield biased estimates of the effects of size on organizational outcomes, due to the typically strong positive correlation between the two variables (Barron, West, and Hannan 1994). *Firm Age* was simply calculated as a given year t minus founding year of the firm. Because new ventures with one sole founder might be fundamentally different from those with multiple

[4] Two coefficients are high enough to cause concern, as the correlation between *Years of Prior Working Experience* and *Founder Age* exceeds 0.90. Due to such high correlation between the two, it may cause potential problem of multicollinearity that inflates the variance of the model. Thus, I omitted *Founder Age* in the statistical models.

founders, consistent with prior literature (Sine, Mitsuhashi, and Kirsch, 2006), I control for the former with the variable *Sole Founder Venture,* which is coded 1 if a firm had only one founder, and zero otherwise. In categorizing new ventures, incumbent-backed ventures are separate legal entities with formal ties to the incumbents (Agarwal, Echambadi, Franco, and Sarkar, 2004), and represent a hybrid between start-up and diversifying entrants. I coded *Incumbent Backed Ventures* 1 if new ventures are joint venture or subsidiaries. Prior literature maintains that firms that are vertically integrated will lose economies of scale and be forced to manage more complex routines (Randall and Ulrich, 2001), thus affecting search strategy. I controlled for *Internalization* with an indicator variable that takes the value of 1 if the firm not only manufactures cells, but also packs and assembles cells into battery, and 0 if the firm only focuses on cell manufacturing activity. I collected information on boundary choices at founding from firms' websites and industry publications. I also ensured that these boundary choices remained unchanged, making sure there were no switches between internal and external modes within the sample firms. Previous literature also suggests that resource availability affects founders' decision making (Helfat and Lieberman, 2002). Because a founder with a resource slack should feel less pressure for expanding their search boundaries, thus spend more on diverse search to find ways of how to reconfigure their knowledge, access to financial resources will affect new ventures' search strategy (Gruber, MacMillan, and Thompson, 2008). I utilized a dummy variable – *VC Funding* – to indicate whether new ventures acquired such seed funding. This variable has a value of 1 if the firm acquired seed funding, and 0 otherwise.

At the environmental level, I controlled for *Annual Industry Growth*$_{t-1}$. Research on industry evolution posits that firms' strategic decision making is influenced by the growth stage of their industry (Agarwal and Bayus, 2002; Carroll, Bigelow, Seidel, and Tsai. 1996). This variable was measured for year t when the dependent variable was measured for year t + 1. I also controlled for time period effects due to changes in policies and regulations related to the LIB industry using *Year Dummy* variables pertaining to the different years in which firms operated. The omitted category was 1991 – the first year of the study period. These variables allowed me to control for factors specific to a particular year that might affect firms' search pattern for that year. Lastly, since national economic situations and culture may affect new ventures' strategic decision making, I controlled for the country in which the firm was founded by creating a dummy variable – *US* – which I coded 1 if new ventures are located in the United States, and 0 otherwise.

Model Specification

My data structure is yearly panel data that is unbalanced, implying that the number of observations varies by firm, as some firms leave the sample earlier than others. The unit of analysis is the business year, with 88 firms yielding 1068 business-years. Since the first dependent variable – *Search Breadth* is a count variable and takes on integer values only, I can choose between the Poisson and negative binomial regression models. After checking the potential over-diversion problem, it turned out that the negative binomial model is more appropriate than the Poisson model in my study. This model relaxes the restrictive assumption of mean and variance equality inherent in the Poisson model and also accounts for omitted variable bias (Walker, Kogut, and Shan, 1997).

The second dependent variable in the regression model – *Search Depth* is censored, since the variable is a ratio ranging between 0 (depth) and 1 (shallowness). Accordingly, a Tobit model is appropriate (see Greene, 2003: 905–926). Moreover, as the assumption of normality of residuals is satisfied in our case, the maximum likelihood estimators of the standard Tobit model are consistent. Thus, alternative specification of the Tobit model that resolve the departure of the distributions from normality (i.e. Log normal distribution for the residual of the Tobit model) (see Greene, 2000: 916).

I estimated models using firm random effects for three reasons: (1) significant unobserved heterogeneity was present (Greene, 2003), (2) Hausman specification tests were not significant, supporting the use of random effects, and (3) significant serial correlation was not present.

Results

Table 1 presents a descriptive statistics and correlation matrix for the variables used in the analyses. Although there are many pairs of variables that show significant pairwise correlations, in general, correlation between the variables is moderate. In addition, my models do not suffer from multicollinearity issues, as the variance inflation factor (VIF) for *Year Dummy* is the highest (3.02), which is below the recommended cutoff level of 10 (Neter, Kutner, Nachtsheim, and Wasseman, 1996).

For all models, Huber-White robust standard errors are reported, and all significance levels are for two tailed tests. Table 2 shows the results from a Negative Binomial regression analysis of new venture search breadth strategy. Model 1 contains control variables only, and Model 2 adds *Founder Relevant Industry Experience* to test the effect of founder relevant industry experience on search breadth. Supporting Hypothesis 1a, the coefficient of *Founder*

Relevant Industry Experience is positive and significant (β = 1.24, p<0.01), suggesting that new ventures whose founder(s)' prior working experience is relevant to LIB industry tend to search broadly. Model 3 adds *Founder Diverse Industry Experience* to Model 1 to test the effect of founder diverse industry experience on search breadth. As postulated in hypothesis 1b, new ventures whose founder(s)' prior working experience is diverse tend to search narrowly (β = -0.58, p < .05).

Table 3 shows the results from a Tobit regression analysis of new venture search depth strategy. Model 1 contains control variables only, and Model 2 adds *Founder Relevant Industry Experience* to test the effect of founder relevant industry experience on search depth. Hypothesis 2a is supported as the model indicates that the coefficient of founder relevant working experience on shallow search is negative and marginally significant (β = -0.09, p < 0.1). This implies that new ventures whose founder(s)' prior working experience is relevant to the LIB industry tend to search deeply. Model 3 adds *Founder Diverse Industry Experience* to Model 1 to test the effect of founder diverse industry experience on search depth. Supporting Hypothesis 2b, new ventures whose founder(s)' prior working experience is diverse tend to search shallowly (β = 0.09, p < .10). Taken together, the results from Table 2 and Table 3 indicate that founders with relevant industry experience invest in broader and deeper searches, whereas founders with diverse industry experience tend to prefer narrow and shallow searches.

Robustness Checks

A LIB cell is made of four major components: Cathode, Anode, Separator, and Electrolyte. Among these parts, technological choices in cathode materials differentiate LIB cell performance in terms of power and density (Wagner et al, 2013). In this sense, the total number of markets new ventures potentially enter is largely determined by the cathode materials they use to manufacture a LIB cell. For example, if firm A uses NMC cathode materials in cell manufacturing, we can expect its targeted market to be electric vehicles, whereas if firm B uses LCO cathode materials in cell manufacturing, we can expect its targeted market to be consumer electronics. Figure 4 shows the historical trend of patenting activity for the five most commonly used cathode materials – LCO, spinel, NMC, olivine, and NCA. As the figure illustrates, each cathode's invention year is significantly different. For example, while LCO was invented in 1980, NMC, the newest cathode material, was invented in 1999. This means that all five cathodes were not available until 1999, implying that the number of available markets new ventures can enter before 1999 was fewer than after 1999. Given the difference in terms of total number of markets before and after 1999, I restricted my observation of new venture search strategies to only include those after 1999 to control for this crucial difference in market environments. After excluding new ventures' search strategies before 1999, the total number of observations for 88 new ventures was 995.

Table 4 shows the results from a Negative Binomial regression analysis of new venture search breadth strategy. Model 1 contains control variables only, and Model 2 adds *Founder Relevant Industry Experience* to test the effect of founder relevant industry experience on search breadth. Supporting Hypothesis 1a, the coefficient of *Founder Relevant Industry Experience* is positive and significant (β = 1.20, p<0.01), suggesting that new ventures whose founder(s)' prior working experience is relevant to LIB industry tend to search broadly. Model 3 adds *Founder Diverse Industry Experience* to Model 1 to test the effect of founder diverse industry experience on search breadth. As postulated in hypothesis 1b, new ventures whose founder(s)' prior working experience is diverse tend to search narrowly (β = -0.58, p < .05).

Table 5 shows the results from a Tobit regression analysis of new venture search depth strategy. Model 1 contains control variables only, and Model 2 adds *Founder Relevant Industry Experience* to test the effect of founder relevant industry experience on search depth. Hypothesis 2a is supported as the model indicates that the coefficient of founder relevant working experience on shallow search is negative and marginally significant (β = -0.11, $p < 0.01$). This implies that new ventures whose founder(s)' prior working experience is relevant to the LIB industry tend to search deeply. Model 3 adds *Founder Diverse Industry Experience* to Model 1 to test the effect of founder diverse industry experience on search depth. Supporting Hypothesis 2b, new ventures whose founder(s)' prior working experience is diverse tend to search shallowly (β = 0.07, $p < .10$).

Discussion

By employing a rich longitudinal data set within a high-tech industry from the point of its emergence, this study has begun to shed light on a key issue in entrepreneurship and technological search: the effect of founder characteristics on technology search strategies after entry into a focal industry. In this study, I assert that in order to understand the technological search strategies within firms, scholars should attend to the different types of founders' prior experience gained before entry into a focal industry. Because new ventures face significant uncertainty regarding the correct technological path to adopt, they attempt to solve this problem through a unique strategy based on the experiential knowledge and expertise possessed by their founders (Siemsen, 2008). In response to calls for a systematic understanding of what drives new ventures to make different search strategy choices in a high-tech industry with a high level of volatility and turbulence, this study advances the literature by considering how and to what extent individual-level factors shape the way new ventures formulate their technology search paths.

Contributions and Implications

My findings reveal a number of key insights for the literature on technological search, entrepreneurship, and industry evolution. First, my study contributes to technological search literature, as it begins to investigate individual-level determinants of firm heterogeneity in the technology search strategies of new ventures, which is an under-explored area in the domain of search literature. Although it is paramount to examine the antecedents of firms' various search strategies in order to understand the whole processes of what determines strategic choices and how such different choices affect innovative performance, the literature thus far has mainly focused on the performance implications of search strategies (Katila and Ahuja, 2002; Laursen and Salter, 2006; Keupp, Palmie, and Gassmann, 2011; Terjesen and Patel, 2015). My study fills this gap in technological search literature.

Second, this research has important implications for research on entrepreneurial decision-making. So far, the extant research on entrepreneurship has focused on firms during their early years of operation, and thus likely overlooks the critical role founder prior experience plays in forming the seed of a new venture's evolution and long-term prospects (Beckman, 2006, Shane, 2000; Shane and Khurana, 2003). I explore the significant influence founder pre-entry experience exerts on formulating the search trajectories of new ventures. My research also provides important insights into evolutionary economics. Thus far, extant research on evolutionary economics has examined either how pre-entry experience shapes new ventures' initial strategies (Helfat and Lieberman, 2002; Helfat and Raubitschek, 2000) or it has delved into the relationship between pre-entry experience and firm performance (Agarwal et al, 2004; Klepper, 2002; Wenting, 2008; Simons and Roberts, 2008, Chatterji, 2009). The literature therefore leaves the effect of pre-entry experience on post-entry strategies, including the evolution of technological choices, within a black box. By furthering inquiries into the effect of pre-entry experience on search strategy over time, my study fills significant gaps in evolutionary economics.

Limitations and Future Research

Since this study utilizes patent data to trace the technological search behavior of researchers inside firms within a single industry, it limits the study in several ways. First, while patent data allow me to trace innovative behavior over time, it does not cover all the innovative activity of the sample firms. Indeed, many inventions are not covered by patents. Second, firms' search strategies can be observed only in the years that they have filed for a patent, since the variables are constructed based on the patents filed by the researcher that year. This implies that the search behavior of firms which are not filed as patents cannot be observed. Although the LIB industry setting alleviates these two problems, given that protecting intellectual property through patents is important in this industry (Wagner et al, 2013), the limitations are not completely eliminated.

In addition, my research is based on a single industry that is approaching maturity but has not yet arrived at the shake-out stage. Ideally, an examination of my theoretical predictions through the entire life of an industry would make for a more complete story, thus increasing the power of generalizability. Thus, replicating this study in other industries would be one promising venue for future research.

Founder origin also needs to be studied more specifically. Although I tracked founders' working trajectories before entry into the LIB industry, the operationalization of founder relevant industry experience can be detailed further. From the sample, relevant industry experience incorporates both experience from upstream industries (i.e. electrical engineering, chemical industries) and downstream industries (i.e. battery, energy industries). Given that the content and scope of the knowledge gleaned from upstream and downstream industry experiences is quite different, further studies could look into the distinctive impact of different types of founder relevant industry experience on the search strategies of new ventures.

Although the single industry setting as well as random effects model allow me to control for many unobserved factors that may influence the search process, my findings are still subject to unobserved heterogeneity. For example, unobserved factors such as behavioral and personality characteristics unique to different founders may play a role in their decisions to broaden or deepen the knowledge bases of their new ventures. Incorporating founders' behavioral patterns, such as their degree of risk aversion and their personality into this vein of research would further enrich the literature.

Tables and Figures

Table 4 Descriptive Statistics and Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tech Breadth	1											
Tech Focus	0.03*	1										
Relevant Industry Experience	0.03	0.09*	1									
Diverse Industry Experience	-0.02	-0.10*	-0.23*	1								
Gender	0.03	0.02	-0.07*	0.06*	1							
Years of Working Experience	-0.03	0.06*	0.42*	-0.18*	-0.04	1						
Firm Size	0.15*	-0.05*	0.17*	0.05	0.15*	0.04	1					
Firm Age	0.31*	0.10*	0.08*	-0.05	0.12*	0.01	0.63*	1				
Sole Founder Venture	0.06*	-0.02	-0.11*	0.15*	0.06*	-0.03	0.25*	0.08*	1			
Incumbent Backed Venture	-0.03*	0.01	0.10*	-0.11*	0.09*	-0.13*	-0.16*	-0.18*	0.10*	1		
Internalization	0.10*	0.02	-0.18*	0.05	0.12*	-0.17*	0.38*	0.21*	0.20*	0.01	1	
VC Funding	-0.04*	0.16*	0.08*	-0.12*	-0.06*	0.29*	-0.35*	-0.04*	0.17*	-0.35	-0.20*	1
US	-0.04*	0.23*	-0.01	0.04	-0.18*	-0.03	-0.25*	-0.04*	-0.11*	-0.02	-0.02	0.24*

Note: N=1,068. Starred pairwise correlations are significant at least at 0.05 level.

Table 5 Results of Random-Effects Panel Negative Binomial Regression Analysis Predicting New Venture Search Breadth

VARIABLES	(1) Search Breadth	(2) Search Breadth	(3) Search Breadth	(4) Search Breadth
Founder Relevant Industry Experience		1.243***		1.068***
		(0.287)		(0.306)
Founder Diverse Industry Experience			-0.583**	-0.261
			(0.281)	(0.289)
Founder Gender	-0.243	0.442	0.0863	0.121
	(0.788)	(0.754)	(0.775)	(0.284)
Founder Years of Prior Working Experience	0.00470	-0.0137	0.0107	-0.0217
	(0.0119)	(0.0127)	(0.0123)	(0.0333)
Firm Size	0.253***	0.287***	0.254***	0.278***
	(0.0703)	(0.0705)	(0.0701)	(0.0709)
Firm Age	0.0346	0.0408	0.0341	0.0420
	(0.0289)	(0.0284)	(0.0284)	(0.0278)
Sole Founder Venture	-0.654*	-0.155	-0.369	-0.170
	(0.358)	(0.351)	(0.371)	(0.362)
Incumbent Backed Venture	0.414	0.0362	0.457	0.174
	(0.355)	(0.365)	(0.352)	(0.377)
Internalization	-0.180	-0.0107	-0.121	-0.00877
	(0.262)	(0.260)	(0.264)	(0.266)
VC Funding	-0.326	-0.265	-0.241	-0.302
	(0.322)	(0.306)	(0.317)	(0.320)
US	1.209***	1.286***	1.425***	1.332***
	(0.279)	(0.272)	(0.295)	(0.293)
Year Dummy	INCLUDED	INCLUDED	INCLUDED	INCLUDED
Constant	-20.25	-23.76	-20.35	-22.48
	(9,714)	(21,157)	(7,340)	(11,168)
Observations	1,068	1,068	1,068	1,068
Number of Firms	88	88	88	88

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

Table 6 Results of Panel Tobit Regression Analysis Predicting New Venture Search Depth

VARIABLES	(1) Reverse of Search Depth	(2) Reverse of Search Depth	(3) Reverse of Search Depth	(4) Reverse of Search Depth
Founder Relevant Industry Experience		-0.0907*		-0.0742
		(0.0464)		(0.0471)
Founder Diverse Industry Experience			0.0876*	0.0707
			(0.0460)	(0.0466)
Founder Gender	-0.0850	-0.0938	-0.0980	-0.103
	(0.104)	(0.102)	(0.102)	(0.101)
Founder Years of Prior Working Experience	0.00251	0.00282	0.00140	0.00187
	(0.00225)	(0.00221)	(0.00228)	(0.00227)
Firm Size	-0.0218	-0.0176	-0.0242*	-0.0203
	(0.0141)	(0.0140)	(0.0139)	(0.0139)
Firm Age	-0.0132**	-0.0149***	-0.0132**	-0.0146***
	(0.00545)	(0.00541)	(0.00535)	(0.00535)
Sole Founder Venture	-0.0149	-0.0276	-0.0301	-0.0375
	(0.0511)	(0.0505)	(0.0508)	(0.0503)
Incumbent Backed Venture	0.0340	0.0414	0.0557	0.0576
	(0.0572)	(0.0562)	(0.0573)	(0.0565)
Internalization	0.0144	-0.00770	0.0178	-0.00101
	(0.0479)	(0.0482)	(0.0470)	(0.0479)
VC Funding	-0.0819*	-0.0854*	-0.0773*	-0.0810*
	(0.0461)	(0.0452)	(0.0453)	(0.0447)
US	-0.177***	-0.186***	-0.183***	-0.190***
	(0.0479)	(0.0472)	(0.0472)	(0.0467)
Year Dummy	INCLUDED	INCLUDED	INCLUDED	INCLUDED
Constant	1.558***	1.616***	1.572***	1.617***
	(0.345)	(0.345)	(0.343)	(0.344)
Observations	1,068	1,068	1,068	1,068
Number of Firms	88	88	88	88

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

Table 7 Results of Random-Effects Panel Negative Binomial Regression Analysis Predicting New Venture Search Breadth with Sample Selection

VARIABLES	(1) Search Breadth	(2) Search Breadth	(3) Search Breadth	(4) Search Breadth
Founder Relevant Industry Experience		1.199***		1.057***
		(0.294)		(0.313)
Founder Diverse Industry Experience			-0.577**	-0.288
			(0.288)	(0.296)
Founder Gender	-0.167	0.460	0.164	0.581
	(0.791)	(0.762)	(0.782)	(0.768)
Founder Years of Prior Working Experience	0.00470	-0.0132	0.0103	-0.00813
	(0.0121)	(0.0130)	(0.0125)	(0.0137)
Firm Size	0.278***	0.309***	0.279***	0.301***
	(0.0716)	(0.0715)	(0.0714)	(0.0720)
Firm Age	0.0337	0.0417	0.0322	0.0395
	(0.0310)	(0.0309)	(0.0306)	(0.0306)
Sole Founder Venture	-0.538	-0.0998	-0.251	-0.0193
	(0.363)	(0.356)	(0.379)	(0.375)
Incumbent Backed Venture	0.303	-0.0381	0.340	0.0917
	(0.362)	(0.374)	(0.358)	(0.388)
Internalization	-0.173	-0.0213	-0.118	0.00766
	(0.265)	(0.263)	(0.267)	(0.265)
VC Funding	-0.418	-0.366	-0.334	-0.346
	(0.330)	(0.313)	(0.325)	(0.313)
US	1.277***	1.345***	1.488***	1.485***
	(0.280)	(0.276)	(0.298)	(0.299)
Year Dummy	INCLUDED	INCLUDED	INCLUDED	INCLUDED
Constant	-2.736**	-4.407***	-3.397***	-4.735***
	(1.229)	(1.200)	(1.221)	(1.219)
Observations	995	995	995	995
Number of Firms	88	88	88	88

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

Table 8 Results of Panel Tobit Regression Analysis Predicting New Venture Search Depth with Sample Selection

VARIABLES	(1) Reverse Search Depth	(2) Reverse Search Depth	(3) Reverse Search Depth	(4) Reverse Search Depth
Founder Relevant Industry Experience		-0.114***		-0.102**
		(0.0425)		(0.0432)
Founder Diverse Industry Experience			0.0727*	0.0511
			(0.0415)	(0.0413)
Founder Gender	-0.0585	-0.0733	-0.0749	-0.0833
	(0.0961)	(0.0929)	(0.0950)	(0.0925)
Founder Years of Prior Working Experience	0.00186	0.00272	0.00144	0.00234
	(0.00221)	(0.00214)	(0.00218)	(0.00215)
Firm Size	-0.0153	-0.00983	-0.0171	-0.0116
	(0.0130)	(0.0127)	(0.0128)	(0.0126)
Firm Age	-0.00614	-0.00820*	-0.00587	-0.00780
	(0.00511)	(0.00498)	(0.00503)	(0.00495)
Sole Founder Venture	0.00978	-0.00650	-0.00514	-0.0153
	(0.0474)	(0.0460)	(0.0474)	(0.0462)
Incumbent Backed Venture	-0.0203	-0.00941	-0.00319	0.00150
	(0.0527)	(0.0507)	(0.0526)	(0.0510)
Internalization	0.0100	-0.0170	0.0114	-0.0132
	(0.0441)	(0.0435)	(0.0433)	(0.0432)
VC Funding	-0.0119	-0.0169	-0.00746	-0.0132
	(0.0427)	(0.0411)	(0.0420)	(0.0408)
US	-0.145***	-0.157***	-0.152***	-0.161***
	(0.0441)	(0.0426)	(0.0435)	(0.0423)
Year Dummy	INCLUDED	INCLUDED	INCLUDED	INCLUDED
Constant	1.030***	1.087***	1.051***	1.096***
	(0.156)	(0.152)	(0.154)	(0.152)
Observations	995	995	995	995
Number of Firms	88	88	88	88

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

Figure 4. Historical Trend of Patent Activity for the Various Positive Firm Electrode Materials, as Measured by the Annual Number of

Patent Families. Source PatBase, July 2012

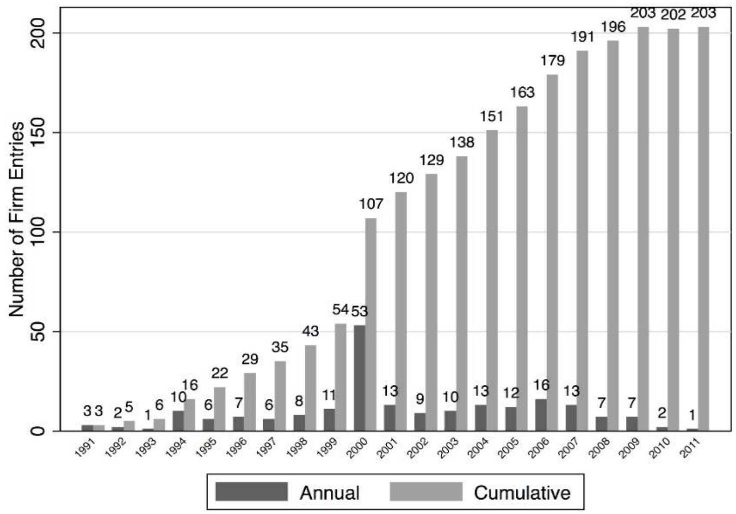
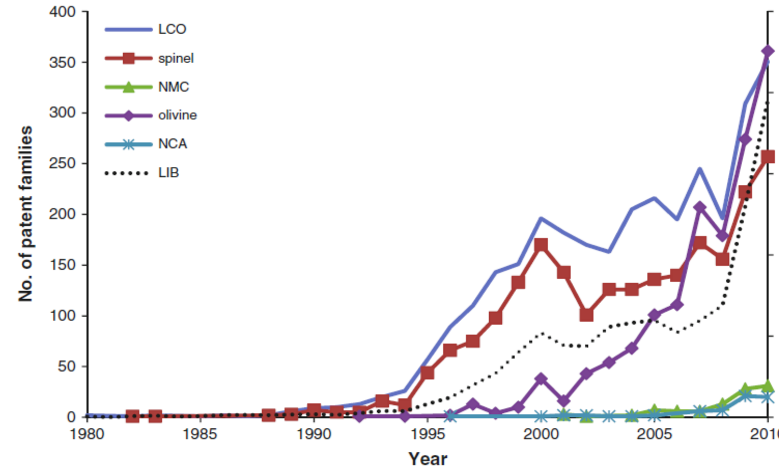


Figure 5. Entrants per Year and Total No. of per Year in the Global LIB Industry



CHAPTER 4: ESSAY THREE

A FIRM'S KNOWLEDGE STRUCTURE AND ITS DISTINCTIVE IMPACT ON THE TYPES OF PRODUCT INNOVATION IN GLOBAL LITHIUM-ION BATTERY INDUSTRY

ABSTRACT

A firm's innovativeness is driven by the structure of its knowledge base. Elaborating on this argument, this study investigates the effect of the level of knowledge decomposability in a firm's knowledge base on two types of product innovation – modular and architecture. The main argument of this study is that the level of knowledge decomposability distinctively affects those two types of new product innovation. I test my predictions using data on 51 worldwide Lithium-Ion Battery (LIB) cell manufacturing firms between 1991 and 2011. My analyses indicate that increasing decomposability is positively associated with modular product innovation, whereas increasing decomposability has an inverted U-shaped relationship with architectural product innovation. By distinguishing between these two types of newly developed products, this study extends a burgeoning literature of how the structural patterns of a firm's knowledge base can affect its product innovation (Guan and Liu, 2016; Wang *et al.*, 2014; Yayavaram and Ahuja, 2008).

Keywords: Knowledge Decomposability, Modular Innovation, Architecture Innovation, and Emerging Industries.

Introduction

Innovation arises from combining or recombining knowledge components (Schumpeter,1934; Fleming, 2001). The literature on recombinant innovation has examined how a firm recombines knowledge components in knowledge domains that are either familiar or new to the firm to improve firm innovation (Ahuja and Katila, 2001; Katila and Ahuja., 2002; Rosenkopf and Nerkar, 2001). This stream of literature has mainly focused on the attributes of a firm's knowledge base including knowledge size, depth, diversity, and the degree of relatedness with other firms' knowledge bases as key drivers for firm innovation (Ahuja and Katila, 2001; Katila and Ahuja, 2002; Carnabuci and Operti, 2013; Mowery, Oxley, and Silverman, 1996).

However, this line of literature has paid less attention to the fact that the way knowledge components are structurally interacted in the firm's knowledge base itself influences firm innovation. Taking a network analogy through which a firm's knowledge base is described as "the set of knowledge components that it possesses and the relationships that it has forged between the knowledge domains to which these components belong" (Yayavaram and Chen., 2015: 377: 18-20), the relationships among knowledge elements within a firm's knowledge base may be more crucial than the attributes of its knowledge base. These relationships can serve as a medium of knowledge flow and guidance for future combinations among knowledge elements and, as a result, enhance firm innovation. Thus, the structural aspect of a firm's knowledge base needs to be fully understood as another key driver for firm innovation.

In responding to this call, there is burgeoning literature that has examined how the structural features of a firm's knowledge base spur firm overall innovation (Guan and Liu, 2016;

Wang *et al.*, 2014; Yayavaram and Ahuja, 2008). However, given that the type of firm innovation can vary – either incremental, modular, architecture, or radical – the next important step is to uncover whether and how the structural patterns in a firm's knowledge base have differential impacts depending on the types of innovation. Although most innovation literature chooses either incremental or radical innovation, traditional categorization of innovation of incremental or radical is incomplete (Henderson and Clark, 1990). Therefore, the research can be advanced through richer categorization of firm innovation by introducing two additional types – modular and architecture. These two types of innovation are more prevalent at the early stages of technological life cycles where firms compete for successful products by experimenting with many different technologies. This is because, at this phase, the successful commercialization of new products requires the firm to synthesize the introduction of new component technologies and reconfiguration of the product to form new linkages between components.

The purpose of this paper is to extend this stream of literature by investigating the differential effect of a firm's particular structural pattern – knowledge decomposability – on two types of firm innovation – modular and architecture – in an emerging high-tech industry. I chose to focus on the decomposability of a firm's knowledge base rather than other dimensions such as cohesiveness, small-world, centralization, or hierarchy (Rivkin *et al.*, 2007) because knowledge decomposability reflects a firm's beliefs about which knowledge components should be combined and, conversely, which knowledge components do not need to be combined. Moreover, given that these beliefs mainly reside in new ventures' pre-entry experience before entering an emerging high-tech industry, the level of knowledge decomposability can also lead to differences in new ventures' ability to combine knowledge components for new product development.

The central argument of this paper is that increasing decomposability of a new venture's knowledge structure is positively associated with modular product innovation, whereas increasing decomposability of a new venture's knowledge structure has an inverted U-shaped relationship with architectural product innovation. I tested my theory and hypotheses on a rich merged data set of patents and Lithium-Ion Battery (LIB) cell products in the context of global LIB cell manufacturing firms between 1991 and 2011, representing the early stages of the industry life cycle (Wagner et al, 2013, Mueller et al, 2015). By investigating the differential effect of a firm's knowledge structure on types of product innovation, this study advances a burgeoning literature that examines how the structural patterns of a firm's knowledge base affect its innovation.

Theory and Hypotheses

I apply a network analogy to firm knowledge structure and treat knowledge as a complex and multidimensional system in which knowledge components are embedded, rather than as a simple attribute of products. In a firm's knowledge network, a "node" is a knowledge component and a "tie" is a combination of two knowledge components in a prior invention (Carnabuci *et al.*, 2009). For theoretical clarity, I only consider a firm's technical knowledge rather than all of its knowledge. Because innovation generally arises from combining or recombining knowledge components (Schumpeter, 1934; Weitzman, 1998), knowledge components are not independent, but are interconnected through joint applications in previous inventions (Fleming, 2001). Thus, the focus here is on a firm's entire knowledge structure and how that leads to new products, rather than on a certain piece of knowledge pertaining to a single product or group of products.

Among structural features of a firm's knowledge base, examining decomposability is important because this dimension highlights that even two firms which possess the same elements of knowledge may still differ in their capability to use that knowledge due to their level of decomposability. Several possible structural patterns delineate a continuum ranging from highly decomposable, nearly decomposable to non-decomposable – also known as integrated (Yayavaram and Ahuja, 2008). In a highly decomposable knowledge base, the ties between knowledge components are dense in some clusters but nonexistent between other clusters. In a nearly decomposable knowledge base (Simon, 1962), some knowledge components are more densely connected with each other than they are with other components, but at the same time, there are some ties that connect clusters to one another. Finally, in a non-decomposable or integrated structure, each knowledge component is strongly tied to each other, so that no groups of elements can be distinguished as a cluster because of the density of ties between groups of elements.

Following Henderson & Clark (1990), I make a conceptual distinction between innovation that creates completely new interfaces between components (architectural innovation) and innovation that introduces new component technologies (modular innovation). Modular innovation involves the introduction of new product components that do not significantly affect the established linkages between components (Langlois and Robertson, 1995). In contrast, architectural innovation changes the product configuration and combines components in new ways without introducing any fundamentally new component technologies (Henderson and Clark, 1990).

The empirical context of the LIB industry represents the early phase of the industry's life cycle, given not many exit events have occurred since its emergence in 1991. Since the LIB industry is technology-intensive, these phases are characterized by a lack of industry-specific knowledge (Gort and Klepper, 1982), and by multiple competing technologies with no consensus concerning the dominant design (Suarez and Utterback, 1995). Moreover, there is severe competition among the distinctive technologies of lithium-ion batteries (Battke et al, 2013), and so far a leading battery technology has yet to emerge in any of the investigated market applications. Taken together, modular and architecture innovations are particularly significant in this context compared to in the more matured phases of an industry's life cycle.

The linear effect of decomposability on modular innovation

Prior research suggests that innovation often emerges from the interplay between specialized and broad knowledge, and the integrative mechanisms that connect the two (March, 1991; Katila and Ahuja, 2002; Yayavaram and Ahjua, 2008). Specialized knowledge fosters deep understanding of a specific area, and involves the repeated application of a few elements (Katila and Ahuja, 2002). In contrast, broad knowledge enables firms to get exposed to divergent ideas and applications, and distinctive new combinations of a given set of elements (March, 1991; Katila and Ahuja, 2002). Meanwhile, integrative mechanisms ensure that the deep knowledge acquired through specialization is matched with the novel applications identified through broad knowledge.

Compared to other types of firm innovation, however, modular innovation is more effective when combined with specialized knowledge. To acquire such knowledge, firms need to refine and improve existing technological combinations to discover new contexts in which such combinations can be applied. Through the repeated use of existing ties among knowledge components, a firm is able to delve deeper into a firm's existing repertoire (Argyres and Silverman, 2004; Katila and Ahuja, 2002). The acquisition of deep specialized knowledge in one specific domain can be realized most through a decomposable knowledge structure, as such firms are capable of systematically refining existing knowledge combinations to solve new problems and develop new applications, thus achieving localized innovation within specific knowledge clusters.

Meanwhile, modular innovation requires less broad knowledge, which can be acquired by searching for distinctive new combinations outside existing sets of local knowledge. For example, both cathode and anode are major components to run LIB cells, and technological advancement in both components significantly improves the overall performance of LIB cells. However, to develop more technologically advanced cathodes, a firm would not have to consider potential combinations with knowledge clusters related to anode. Rather, considering combinations within cathode knowledge clusters is enough to produce a more advanced cathode. Further, because the degree of recombination with other disconnected knowledge elements is lower, modular innovation also requires less of an integration mechanism to link newly identified knowledge components across clusters.

Although a high level of decomposability lacks integration mechanisms to link various knowledge across clusters, it does not limit the likelihood of combination within existing clusters. Rather, there is a negative effect of low decomposability on modular innovation. In less decomposable knowledge bases, when firms consider any change in one knowledge component, they must also take into consideration the effect of the change on all the other related components. Such a high degree of interdependency increases the complexity of the search process and makes even a local search ineffective.

Taken together, when any integration mechanisms exists between clusters of elements, then the search for better configurations in one cluster is partly tied to the search for better configurations in the other cluster. However, in a decomposable knowledge base where this integration device is missing, this is less problematic, since improvements in a local knowledge cluster may be sufficient to develop specialized knowledge, leading to modular innovation.

Thus,

Hypothesis 1: Increasing decomposability of knowledge structure will be positively associated with modular product innovation.

The curvilinear effect of decomposability on architecture innovation.

A firm that aims to be successful in developing new product linkages needs to adopt a focused system as well as breadth and depth in technological problem solving (Henderson and Clark, 1990). In other words, a firm's architectural innovation hinges both on the development of specific routines for technology integration and on the possession of a broad and deep technological understanding, all of which allow the firm to facilitate combinations of knowledge components that often cut across knowledge domains.

These three mechanisms – exposure to new ideas, deep understanding of a specific knowledge domain, and integration – can be realized more effectively with nearly decomposable knowledge bases compared to those with an extremely low or high levels of decomposability. Extremely low levels of decomposability will limit the breadth of knowledge and make effective recombination of any newly identified elements into successful innovation more complex and difficult. Meanwhile, although an extremely high level of decomposability is advantageous for generating deep specialized knowledge, it provides no integration mechanisms to link specialized knowledge across the clusters within a firm's knowledge base. More importantly, without integration between clusters in highly decomposable knowledge bases, any changes in one knowledge cluster cannot be detected by individuals involved in other clusters, even if there is a significant effect between the two clusters. As a result, although a new technology developed in one cluster may have a positive link with another, knowledge transfer will not take place between the two clusters in knowledge bases with an extremely high level of decomposability.

Given that specialization needs to be accompanied by integration to achieve architecture innovation (Henderson and Clark, 1990), moderate levels of decomposability can correct these deficiencies by allowing enhanced exploration of new knowledge and providing integrative mechanisms to link the new knowledge discovered through this broad search with specialized knowledge, thus making effective combinations possible.

Thus,

Hypothesis 2: Increasing decomposability of a firm's knowledge structure will have an inverted U-shaped relationship with architectural product innovation.

Data and Methodology

Industry Setting and Construct Validity

The empirical setting for this study is the global Lithium-Ion Battery (LIB) Industry from 1991 to 2011. The LIB cell manufacturing industry initially emerged in 1991 with the development of the first commercial LIB by Sony Corporation. Figure 6 depicts the pattern of entry into the LIB industry. The number of entrants rapidly increased from around 1999, peaked in 2009, and declined gradually thereafter as a result of intense competition, the global financial crisis, and weakening governmental support. However, the observed entry pattern shows that the industry has not yet experienced a major shake-out, with few exit events occurring during the studied period. Moreover, since there are multiple competing technologies and no dominant design yet (Suarez and Utterback, 1995), the industry represents the early stage of an industry life cycle (Wagner et al, 2013, Mueller et al, 2015).

The LIB cell manufacturing industry represents an ideal setting for this study for several reasons. First, the high research and development (R&D) intensity of the LIB industry implies that the industry is characterized by constant technology change (Wagner et al, 2013), and that most LIB firms routinely patent their inventions (Battery University, 2009). This is well suited to a study of the changes in a firm's knowledge base. Second, in the early stage in industry life cycle (Wagner et al, 2013, Mueller et al, 2015) both modular and architecture innovations are pervasive, as firms must actively develop knowledge about components as well as knowledge of how these components can be integrated (Henderson and Clark, 1990). This allowed me to easily observe the two types of product innovation – modular and architecture.

A LIB cell consists of four components: cathode, anode, separator, and electrolyte. Within LIB cell research, the current goal of the battery community is to develop more advanced cathodes, as firms' technological choices in cathodes differentiate LIB cell performance in terms of power, density, and life cycle by providing higher potentials and larger specific charges (Battery University, 2012). Using silicon as an anode material is nearly optimal so only minor improvements can be gained by changing this material. The separator is not a core component within LIB cells, given that the number of patents for separators is the smallest and the growth rate in the number of patents for separators are lowest among four components. Most LIB cells available in the market utilize non-aqueous electrolyte, where lithium salts are dissolved in aprotic organic solvents (Winter, 2009). Taken together, given that cathodes are the major component that can enhance the performance of LIB cells, firms are trying to develop more technologically advanced cathodes to apply to their existing LIB cell designs. For example, Sony initially produced LIB cells with Lithium Cobalt Oxide (LCO) as a cathode, then it later developed Lithium Iron Phosphate (LFP) cathode to enhance the overall performance of its LIB cells in terms of power, density, and life cycle. It is important to keep in mind that plugging an advanced cathode into an LIB cell does not require changes in cell architecture itself. For example, the change from LCO to LFP cathodes will not necessarily require a change in LIB cell design from cylindrical to prismatic. In other words, newly developed LFP cathodes can be applied to existing cylinder LIB cell designs to create better-performing cells.

Moreover, developing new cathodes enables new ventures to enter into promising markets with high consumer demand. For example, in order to enter the electric vehicle market, firms require more advanced cathodes such as nickel manganese cobalt oxide (NCM) cathodes.

With less advanced cathodes such as LCO, firms can only enter into the more or less stable consumer electronic market. If firms would like to expand their market scope from one to the other, developing a more advanced NCM cathode is a necessity.

Given that modular innovation is defined as (Henderson and Clark 1990) improving product innovativeness by changing key components within products that do not significantly affect the product architecture, its key feature is that it allows firms to produce families of products based on the same overall product architecture, thereby helping them to satisfy heterogeneity in market demand. Therefore, technological advances in cathode components has a high level of construct validity with the concept of modular innovation.

Meanwhile, depending on how LIB cells are packaged, there are four different possible cell designs – cylindrical, button, prismatic, and pouch. As Figure 7 shows, the way the four LIB components are integrated looks quite different among the four types of cell shapes. These differences also lead to variations of performance in terms of energy density and energy efficiency, and duration. For example, while the cylindrical cell design has good cycling ability and offers a long calendar life, this design has low packaging density, leading to inefficient use of space (Battery University, 2013). In contrast, the prismatic cell design is space-efficient; however, this design has a shorter life cycle than the cylindrical design. By using laminated architecture, the pouch cell design uses conductive foil-tabs which are welded to the electrodes and brought to the outside in a fully sealed way, thus making the most efficient use of space. Taken together, in the sense that the performance of LIB cells is also determined by choices of cell design, the number of cell designs that a firm possesses has a high level of construct validity with the concept of architecture innovation.

Data

The data-gathering process of the independent variable – the level of decomposability in each sample firm's knowledge base – began by counting the total number of 268 LIB firms listed in the battery database of Shmuel De Lion Energy, Ltd., to which I subscribe. Second, I searched through Espacenet, Google Patents, Orbis, and firms' websites to identify the number of firms with patents. Third, I used *Who Owns Whom* corporate directories to obtain information on the ownership structure of LIB firms. After identifying the 225 LIB firms with patents, I used PATSTAT to retrieve their patents. The advantage of PATSTAT compared to USPTO is that it gathers data from all major patent offices including USPTO, European Patent Office (EPO), Japan Patent Office (JPO), State Intellectual Patent Office (SIPO), and Korea Patent Office (KPO). Given the dominance of Asian countries in manufacturing LIB cells, the sole use of patents granted in USPTO cannot capture patent activities industry-wide (see Figure 8). To minimize the influence of right censoring, I ended the study period in 2013 to allow sufficient time for the approval of patent applications that sample firms submitted during the sample period. As a result, the total number of observations from 225 firms is 1,055,596. To generate my independent variable – the level of knowledge decomposability of each firm – I first used PATSTAT's technology class data of Cooperative Patent Classification (CPC) to create the sample firms' knowledge bases. To identify LIB-related patent classes, I started by looking at all the classes that were assigned to all the patents of all the firms in our sample. Next I ranked the CPC by the number of patent classes to which firms were assigned and considered the top 100 CPC to be LIB classes. In the process, I excluded the patent classes assigned to large companies in our sample, including Panasonic, Sony, and Samsung, due to their high level of patent activities across various industries not related to

LIBs. Through this process, the total number of observations was reduced to 349,813 from 200 firms.

Although patent-based measures are widely accepted as proxies of various types of firm innovative outputs (Griliches, 1998), challenges in using patent-based measures still remain: patent values are often highly skewed, and patents cannot capture the innovativeness of a commercialized product sold to users (Gambardella et al., 2008; Gittelman, 2008; MingJi and Ping, 2014) since the commercial value that is generated from a patent depends on several factors beyond its technological usefulness, such as whether the firm is able to market the invention and then protect and appropriate the value that is generated. More importantly, on a conceptual level, a patent is the fundamental knowledge through which new products have been developed, rather than new commercialized products themselves. To overcome such challenges, I decided to collect detailed information on over 18,000 LIB cell products through LIB cell technological specification documents from Shmuel de Lion Energy, Lexis-Nexis Academic press announcements, and firm websites to generate my dependent variables. I ran multiple steps to collect information on cathode materials, cell shapes, and the launch year of each LIB cell. First, I conducted keyword-based search including the names of five types of cathodes, the names of four types of cell shape, and any four-digit number from full text of the each file through my designed algorithm. As the majority of information on cathode and cell type was not extracted through this algorithm, and most four-digit numbers extracted did not represent information on the launch year of LIB cells, next, I manually checked each PDF file where a LIB cell's cathode materials and cell shapes, its launch each year could be found. As the majority of the PDF files did not provide such information, however, after this search 5,000 LIB cells remained in my sample. Since a good portion of sample firms have developed multiple LIB cells with a combination of one particular cathode (i.e. LCO) and cell shape (i.e. cylinder) during one particular year, the total number of observation shrank accordingly. These sampling criteria resulted in a sample of 66 and 65 firms with 925 (Cathode) and 915 (Cell type) observations, respectively.

Finally, I collected data from VentureXpert, the Department of Energy, local newspapers, and industry trade journals to control for firm- and environmental-level variances. After merging the data set including independent, dependent, and control variables, the final sample included 51 global LIB cell manufacturing firms and 409 observations, plus 50 global LIB cell manufacturing firms and 402 observations, which I then used to investigate the distinctive effect of a firm's knowledge structure on its type of innovation during the sample period.

Measures

Dependent Variables

In this study, two dependent variables, namely modular and architecture innovations, were developed based on detailed LIB cell data. As I noted earlier, cathode material represents a core knowledge component of LIB cells, as further advances in cathode materials are essential for battery performance enhancement, which allows firms to consider entering promising markets such as electric vehicle and stationary energy storage. The first dependent variable, ***Modular Innovation***$_t$, is a yearly count variable capturing the accumulated number of firm choices on cathode materials from their founding in year t. The five most commonly used cathode materials are LCO, spinel, NMC, olivine, and NCA. In contrast, cell shapes determine the ways in which all components in LIB cells are integrated and interacted. The second dependent variable, ***Architecture Innovation$_t$***, is a yearly count variable capturing the accumulated number of firms' choices on cell shapes from their founding in year t. The four most commonly used cell shapes are cylinder, button, prismatic, and pouch.

Empirically, I used detailed Lithium-Ion Battery cell data to generate information on these two types of product innovation. As cathode materials represent a core knowledge component of LIB cells, I examined modular innovation based on the number of cathode materials developed by firms. In contrast, as cell shapes describe the way knowledge components are interrelated, I investigated architecture innovation based on the types of cell shapes developed by firms.

Independent Variable

I followed prior research (e.g. Yayavaram and Ahuja, 2008; Yayavaram and Chen, 2015) to generate a measure of ***Decomposability***. To do so, multiple steps are required. First, I began by creating a firm's knowledge base. A firm's knowledge base at t is assumed to consist of all the patents that the firm has accumulated during $t - 3$ to $t - 1$ years. Following Fleming and Sorenson (2001), I also assumed that the technology classes assigned to patents are elements in the firm's knowledge base, and the co-listing of classes is indicative of a recombinant search process. Taking network terms, nodes in a firm's knowledge network are the technology classes assigned to its patents, and a tie between two nodes forms when a patent is developed by using these two nodes. I used PATSTAT's technology class data of Cooperative Patent Classification (CPC) because their class assignments are less prone to bias due to the care PATSTAT takes when classifying patents. Moreover, CPC has been recently introduced and allows technological resolution with unprecedented clarity (Mueller et al. 2015).

To identify LIB-related classes, I looked at the classes that were assigned to all the patents of all the firms in my sample. I ranked the CPC by the number of patent classes to which firms were assigned and then considered the top 100 CPC to be LIB classes. I excluded the patent classes assigned to large companies in my sample including Panasonic, Sony, and Samsung. Due to these firms' high level of divergence in their patent activities spread over various industries, it is possible that a significant portion of the top 100 CPC may include patent classes originating from their patents, which are not relevant to LIB classes. For example, given that the top 10 most frequently used patent classes of Samsung Co. are related to the semiconductor industry, if I rank the CPC purely based on the number of patent classes to which sample firms assigned, fewer LIB-related classes can be included in top 100 CPC. For the next step, I used 100 CPC classes to generate a firm's knowledge base in year *t*, which comprises patents from *t – 3* to *t – 1*. I used a three-year window to minimize the effects of yearly fluctuations in patent applications.

Next, I characterized a firm's knowledge base based on the type of relationship between knowledge elements as coupling, which is defined as the extent to which a firm is likely to combine the elements in two domains, X and Y, when searching for new inventions (Yayavaram and Ahuja, 2008). Using the ratio known as Jaccard's coefficient in cluster analysis (Everitt, 1993: 41), the coupling between technology classes *j* and *k* for firm *i*, $L_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$ can be calculated as

$$L_{i,\, j-k,\, t-3\ to\ t-1} = n_{jk}\ \ / n_j + n_k - n_{jk},$$

where n_j is the number of patents assigned to class j , n_k is the number of patents assigned to class k, and n_{jk} is the number of patents assigned to both classes (Yayavaram and Ahuja, 2008). The coupling matrix $\boldsymbol{L}_{i,j-k,\, t-3 \text{ to } t-1}$, consisting of $L_{i,j-k,\, t-3 \text{ to } t-1}$ for all pairs of domains, represents the firm's knowledge base. This yielded a total number of 1124 100 x 100 adjacency matrices.

From firms' knowledge networks, my measure of the ***level of decomposability*** in the knowledge base is a modification of the clustering coefficient (Watts and Strogatz, 1998; Barabasi, 2002). The clustering coefficient for an element or a node (i.e., a technology class) with k_i ties is defined as $CC_i = n_i / [k_i \text{ x } (k_i - 1)/2]$, where n_i is the number of ties between the k_i neighbors of node i. The denominator is the maximum number of ties that are possible between the k_i neighbors of node i, and the numerator is the actual number of ties that exist. The clustering coefficient for the network, CC, is CC_i averaged over all nodes. The value ranges from 0 to 1, where 0 represents fully decomposable knowledge bases, and 1 represents fully integrated knowledge bases.

Control variables

To minimize alternative explanations and isolate the marginal effects of the explanatory variables, I controlled for several firm- and environment-level variables whose influence on product innovation might be confounded with the explanatory variables. I controlled for organizational-level factors with measures of ***Firm Patent Stock, Firm Technological Diversity, Firm Size, Firm Age, VC Backed Firm,*** and ***Integrator.***

Firm Patent Stock*:* A firm with large patent stocks tends to have deep technological resources and absorptive capacity (Silverman, 1999). The firm can experiment with more recombination and may be more successful at technological searches (Kogut and Zander, 1992), leading to more innovation (Silverman, 1999). I controlled for the number of firm *i*'s patents that were granted to the firm in the past three years and the number of unique citations made by these patents (Ahuja and Katila, 2001).

Firm Technological Diversity*:* Prior literature posits that the manner through which firms develop their technological knowledge significantly affects the degree of firm innovation (Miller, 2004; Garcia-Vega, 2006). A firm's technological diversity represents the extent to which firms draw intensively from specific technological areas, measured using the Herfindahl index (Blau, 1977). I calculated the index using the following formula:

$$D=1-\sum p^{2}_{itk}$$

where P_{itk} stands for the share of firm *i*'s patents in class *k* during the *t-3* to *t-1* period. A three-year moving window may capture a LIB firm's search behavior more accurately, since firms in the sample are those who do not receive many, if any, patents per year (Rothaermel and Deeds, 2004). The minimum value of 0 represents the exclusive usage of one specific technological area in developing new products, whereas values approaching 1 represent a situation where every patent filed by a focal firm is in a distinct patent class of its own. For example, a value of 0.05 indicates a low level of technological diversity, whereas a value of 0.95 indicates a high level of technological diversity. As a robustness check, I calculated another measure of technological diversity during the past five years.

Firm Age: I also included firm age in the models for two reasons. First, as firms grow older, they tend to exploit their existing technological competencies rather than search for new technologies, leading to less firm innovativeness (Sorensen and Stuart, 2000) Second, previous research has shown that models of size effects that fail to control for age yield biased estimates of the effects of size on organizational outcomes, due to the typically strong positive correlation between the two variables (Barron, West and Hannan 1994). *Firm Age* was simply calculated as a given year *t* minus the founding year of the firm.

Firm Size*:* Prior literature suggests that larger firms are less likely to be resource constrained, thus more likely to pursue innovation (Agarwal and Audretsch, 2001; Teece, 1992). I measure the size of the firm by using the number of employees. Firm size is often measured in revenues or market share; however, most samples for the study are privately held companies and therefore do not publicize this information. Thus, measuring firm size through the number of employees provides a reasonable alternative (Shan *et al*., 1994). *Firm Size* was total number of employees, including executives.

VC Backed Firm: Previous literature suggests that a firm with a resource slack may spend more on diverse searches to find ways to reconfigure their knowledge, affecting the level of firm innovation (Helfat and Lieberman, 2002). I utilized a dummy variable – *VC Backed Firm* – to indicate whether firms acquired seed funding. This variable has a value of 1 if the firm acquired seed funding, and 0 otherwise.

Integrator: Prior literature maintains that firms that are vertically integrated will lose economies of scale and be forced to manage more complex routines (Randall and Ulrich, 2001), thus affecting search scope. I controlled for *Integrator* with an indicator variable that takes the value of 1 if the firm not only manufactures cells, but also packs and assembles cells into batteries, and 0 if the firm only focuses on cell manufacturing activity. I collected information on boundary choices at founding from firms' websites and industry publications. I also ensured that these boundary choices remained unchanged, making sure there were no switches between internal and external modes within the sample firms.

I also controlled for the number of cathodes from the prior year by generating a one-year time lagged variable – ***Modular Innovation***$_{t-1}$, and for the number of cell shapes from prior year by generating a one-year time lagged variable – ***Architecture Innovation***$_{t-1}$.

At the environmental level, I controlled for possible time period effects due to changes in policies and regulations related to the LIB industry using ***Year Dummy*** variables pertaining to the different years in which firms operated. The omitted category was 1991 – the first year of the study period. These variables allowed me to control for factors specific to a particular year that might affect firms' product innovation for that year. Lastly, since national economic situations and culture may affect the pace and types of firms' new product development, I controlled for the country in which the firm was founded by creating a dummy variable – ***US*** – which I coded 1 if firms' headquarters are located in the United States, and 0 otherwise.

Model Specification and Estimation

My data structure is yearly panel data that is unbalanced, implying that the number of observations varies by firm, as some firms leave the sample earlier than others. The unit of analysis is the firm year. Either firm-fixed or random effects can be used to control for unobserved firm heterogeneity (Greene, 1997), including differences in motivations to pursue, and abilities to develop new products. I chose to use random effects rather than fixed effects because my key independent measures are change-related measures. Fixed effects estimations are based on within-firm changes in variables, which in this study would imply changes in changes. Because the changes that occur in a firm's knowledge base may not vary sufficiently over time, a fixed effects estimation may be inappropriate. However, as random effects models rely on the assumption that errors and regressors are uncorrelated, I confirmed the appropriateness of the random effects model by conducting a Hausman (1978) test. I also checked for first-order serial autocorrelation in the errors. A random effects model is appropriate since Hausman specification tests were not significant, and significant serial correlation was not present.

The dependent variables – the number of cathode materials and cell shapes that the sample firms develop over time – take on only non-integer values. An ordinary linear regression is not applicable for this type of variable, as it relies on the normality of the dependent variable (Wooldridge, 2002). Poisson regression can be used to model count variables if the assumption of the equality of the conditional mean and variance functions is not violated (Greene 2003). As an over-dispersion problem was not detected, I use a Poisson regression model for my study. I also used robust standard errors to correct for potential non-independence across observations. As a robustness check, I compared the results with ones from GEE models with negative binomial distribution.

Results

Table 1 reports a descriptive statistics and correlation matrix for the variables used in my analyses. Although there are several pairs of variables that show significant pairwise correlations, in general, correlation between the variables is moderate. In addition, my models do not suffer from multicollinearity issues, as the variance inflation factor (VIF) for *Firm Tech Diversity* is the highest (3.46), which is below the recommended cutoff level of 10 (Neter, Kutner, Nachtsheim, & Wasseman, 1996). For all models, Huber-White robust standard errors are reported, and all significance levels are for two tailed tests.

Table 2 presents the results of the panel Poisson regression analysis to test Hypothesis 1. Hypothesis 1 predicts the positive effect of the level of decomposability within a firm's knowledge network on modular innovation. Model 1 contains control variables only, and model 2 adds the level of decomposability. In model 3, I included the alternative variable *Firm Tech Diversity_5yr*, which is the technology diversity obtained in five years prior to the end of year *t*, instead of *Firm Tech Diversity_3yr* obtained in the three year prior to the end of year *t*. Model 4 adds the level of decomposability to Model 3. The negative coefficient of the level of decomposability both in model 2 ($p<0.05$) and model 4 ($p<0.05$) implies that modular innovation is realized with the high level of decomposability, supporting Hypothesis 1. For clarity, with the high level of decomposability, the value reaches toward 0, whereas with the low level of decomposability, the value does toward 1.

Table 3 presents the results of the panel Poisson regression analysis to test Hypothesis 2. Hypothesis 2 predicts the curvilinear effect of the level of knowledge network decomposability on architecture innovation. Model 1 contains control variables only. Model 2 adds the level of decomposability and model 3 adds the square term. In model 4, I included *Firm Tech Diversity_5yr* instead of *Firm Tech Diversity_3yr*. Model 5 and 6 add the level of decomposability and the square term to model 4, respectively. Both Model 3 and 6 indicate strong support for Hypothesis 2 ($p<0.05$; $p<0.01$), indicating that increasing decomposability of a firm's knowledge structure will have an inverted U-shaped relationship with architectural product innovation.

Robustness Checks

In addition to including *Firm Tech Diversity_5yr* above, I performed additional analysis to assess the robustness of my findings. I estimated the full model using a GEE approach where I specified a negative binomial distribution, a log link function, and an exchangeable working correlation matrix and computed robust standard errors (Papke & Wooldridge, 2005). Table 4 and 5 present the results from this analysis for two dependent variables. As shown, the results were consistent with those reported in Table 2 and 3, respectively.

Discussion

My study responds to two important calls that 1) the structural aspect of a firm's knowledge base itself needs to be fully understood as another important key driver for firm innovation (Yayavaram and Ahuja, 2008) and 2) innovation literature will be advanced by examining the various types of product innovation beyond simple categories of incremental and radical innovation (Guan and Liu, 2016). By distinguishing between different types of firm innovation, this study suggests that the structural features of a firm's knowledge base can differentially affect the new product development processes depending on the type of innovation it tries to enhance. More specifically, for modular innovation, more decomposable knowledge structure is always beneficial, whereas for architecture innovation, nearly decomposable knowledge structures are better than either decomposable or integrated ones. This study provides further understanding about how and why the structural properties of a focal firm's knowledge base influence the type of product innovation.

Contributions and Implications

This study contributes to a burgeoning literature investigating how the different types of structural patterns of its knowledge base affect overall firm innovativeness (Guan and Liu, 2016; Wang *et al.*, 2014; Yayavaram and Ahuja, 2008) by distinguishing between different types of firm innovation. The study shows that depending on the type of firm innovation, the same structural pattern in a firm's knowledge base may have distinctive performance implications.

Second, understanding the level of decomposability in a firm's knowledge base will advance the literature on product architecture (Sanchez and Mahoney, 1996; Baldwin and Clark, 2000; Schilling, 2000; Ethiraj and Levinthal, 2004) by showing that firm's innovativeness in terms of modular and architecture innovation can be predicted by the way knowledge components are structurally interacted. This confirms not only that a firm's knowledge structure comes to mirror the internal structure of the product they are designing (Henderson and Clark, 1990), but also shows that the linkage between a firm's knowledge structure and its product architecture reflects the types of innovation a firm decides to follow.

Third, my study supplements social network literature showing how individual collaborative networks influence firm innovation by introducing another type of informal structure – knowledge network. Knowledge network mirrors how knowledge components are connected to or separated from one another, whereas collaborative network enables and constrains the diffusion, transfer, and acquisition of knowledge. My study implies that firm innovation can be achieved through multiple networks, which can be conceptually decoupled.

Limitations and Future Research

I am cognizant of the limitations of my study: First, my empirical analysis is limited to only one high tech industrial context – the LIB industry – which is characterized by multiple competing technologies, no consensus concerning the dominant design (Suarez and Utterback, 1995), and a lack of industry-specific knowledge (Gort and Klepper, 1982). Therefore, my results cannot be simply generalized to other industrial contexts. Considering other industrial contexts would be an interesting avenue to further the literature.

Next, a firm's knowledge bases can display various structural patterns other than decomposability, including cohesiveness, small-world, centralization, or hierarchical (Rivkin *et al.*, 2007). An investigation of the way other structural features of a firm's knowledge base affects the types of firm innovation is another fruitful research area.

Given that innovation activities are embedded into multiple networks including collaborative and knowledge networks within a firm, another promising future direction is to investigate 1) the effect of each network and 2) the joint effect of the two on firm innovation, in general, and the type of innovation, in particular.

In addition, although both hypotheses are supported, one concern is that the number of observations shrunk drastically after merging knowledge network data and LIB product data. As an extension, a future study will include two other major battery technologies – lead-acid and nickel-based – by collecting patents and product data. As all three technologies are comparable in their product architecture, while all three also present sufficient variation in terms of materials, main components, and system design, the rechargeable battery industry is the commercialized potential of an ideal place to investigate the role of knowledge structure in the development paths of new battery products.

Tables and Figures

Table 9. Descriptive Statistics and Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Modular Innovation	1									
Architecture Innovation	0.41*	1								
Level of Decomposability	-0.14*	-0.28*	1							
Firm Patent Stock	0.13*	0.02	0.06*	1						
Firm Technological Diversity	-0.00	-0.08*	-0.18*	0.05	1					
Firm Age	0.27*	0.23*	0.06	0.18*	0.10*	1				
Firm Size	0.01	-0.01	0.04	0.13*	0.10*	0.61*	1			
VC Backed Firm	-0.01	-0.06	0.13*	-0.12*	-0.21*	-0.16*	-0.19*	1		
Integrator	0.29*	0.07*	0.10*	0.19*	-0.01	0.25*	0.28*	-0.01	1	
US	-0.15*	0.15*	0.22*	-0.12*	-0.27*	-0.05*	-0.20*	0.08*	0.03	1

Note: Pairwise correlations with star are significant at least at 0.05 level.

Variables	Mean	Std. Dev.	Min	Max
Modular Innovation	1.44	0.78	1	5
Architecture Innovation	1.33	0.71	1	4
Level of Decomposability	0.78	0.30	0	1
Firm Patent Stock	81.34	133.5	1	834
Firm Technological Diversity	0.69	0.37	0	1
Firm Age	9.19	5.34	1	39
Firm Size	943.16	3496.72	7	20000
VC Backed Firm	0.33	0.47	0	1
Integrator	0.61	0.49	0	1
US	0.41	0.49	0	1

Table 10. Results of Random-Effects Panel Poisson Regression Analysis Predicting Firm Modular Innovation

	Model 1	**Model 2**	**Model 3**	**Model 4**
VARIABLES	Modular Innovation$_t$	Modular Innovation$_t$	Modular Innovation$_t$	Modular Innovation$_t$
Level of Decomposability		-0.0992**		-0.135**
		(0.0442)		(0.0654)
Firm Patent Stock	0.000298***	0.00231	0.000357***	0.00209
	(9.07e-05)	(0.00144)	(9.01e-05)	(0.00143)
Firm Tech Diversity 3ys	-0.0147	-0.0253		
	(0.0301)	(0.0297)		
Firm Tech Diversity 5ys			-0.120**	0.0591
			(0.0581)	(0.0784)
Firm Age	0.00255	0.00320	0.00264	0.00307
	(0.00271)	(0.00276)	(0.00281)	(0.00271)
Firm Size	-5.30e-06**	-4.14e-06	-5.55e-06***	-3.92e-06
	(2.32e-06)	(3.17e-06)	(2.01e-06)	(3.09e-06)
VC Backed Firm	-0.0538**	-0.0673***	-0.0536**	-0.0638***
	(0.0241)	(0.0231)	(0.0241)	(0.0242)
Integrator	0.0465	0.0270	0.0335	0.0282
	(0.0314)	(0.0317)	(0.0323)	(0.0326)
Modular Innovation$_{t-1}$	0.484***	0.486***	0.482***	0.487***
	(0.0175)	(0.0183)	(0.0169)	(0.0187)
US	-0.0741***	-0.0639**	-0.0522**	-0.0633***
	(0.0250)	(0.0258)	(0.0262)	(0.0244)
Year Dummy	Included	Included	Included	Included
Constant	-0.445***	-0.429***	-0.468***	-0.457***
	(0.0466)	(0.0456)	(0.0374)	(0.0356)
Observations	409	409	409	409
Number of Firms	51	51	51	51

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 11. Results of Random-Effects Panel Poisson Regression Analysis Predicting Firm Architecture Innovation

VARIABLES	**Model 1** Architecture $Innovation_t$	**Model 2** Architecture $Innovation_t$	**Model 3** Architecture $Innovation_t$	**Model 4** Architecture $Innovation_t$	**Model 5** Architecture $Innovation_t$	**Model 6** Architecture $Innovation_t$
Level of Decomposability		0.0306	0.312**		0.0404	0.552***
		(0.0285)	(0.130)		(0.0640)	(0.168)
Level of Decomposability Sq			-0.303**			-0.477***
			(0.145)			(0.162)
Firm Patent Stock	0.000239***	0.00182	0.000923	0.000251***	0.00186	0.000838
	(8.29e-05)	(0.00217)	(0.00210)	(9.17e-05)	(0.00298)	(0.00210)
Firm Tech Diversity 3ys	-0.0332	-0.0383	-0.0318			
	(0.0389)	(0.0381)	(0.0400)			
Firm Tech Diversity 5ys				-0.00388	-0.00869	-0.116*
				(0.0353)	(0.0865)	(0.0637)
Firm Age	-0.00314	-0.00274	-0.00250	-0.00321	-0.00279	-0.00244
	(0.00239)	(0.00224)	(0.00242)	(0.00239)	(0.00248)	(0.00239)
Firm Size	-9.01e-06***	-8.04e-06**	-7.46e-06**	-8.73e-06***	-7.51e-06	-6.64e-06**
	(2.52e-06)	(3.95e-06)	(3.57e-06)	(2.43e-06)	(2.74e-05)	(3.29e-06)
VC Backed Firm	-0.0107	-0.0205	-0.0135	-0.00543	-0.0152	-0.0102
	(0.0294)	(0.0294)	(0.0284)	(0.0293)	(0.0476)	(0.0262)
Integrator	0.0247	0.0217	0.0250	0.0221	0.0189	0.0180
	(0.0270)	(0.0266)	(0.0260)	(0.0276)	(0.0205)	(0.0265)
Architecture $Innovation_{t-1}$	0.518***	0.521***	0.518***	0.521***	0.524***	0.517***
	(0.0231)	(0.0247)	(0.0243)	(0.0214)	(0.0286)	(0.0206)
US	-0.0289	-0.0368	-0.0346	-0.0202	-0.0274	-0.0205
	(0.0321)	(0.0320)	(0.0300)	(0.0307)	(0.0512)	(0.0286)
Year Dummy	Included	Included	Included	Included	Included	Included
Constant	-0.471***	-0.459***	-0.469***	-0.513***	-0.508***	-0.507***
	(0.0827)	(0.0800)	(0.0789)	(0.0553)	(0.0848)	(0.0487)
Observations	402	402	402	402	402	402
Number of Firm	50	50	50	50	50	50

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 12. Results of Random-Effects Panel GEE Models with Negative Binomial Distribution Predicting Firm Modular Innovation

VARIABLES	**Model 1** Modular $Innovation_t$	**Model 2** Modular $Innovation_t$	**Model 3** Modular $Innovation_t$	**Model 4** Modular $Innovation_t$
Level of Decomposability		-0.103**		-0.113**
		(0.0432)		(0.0526)
Firm Patent Stock	0.000306***	0.00204*	0.000371***	0.00197*
	(0.000100)	(0.00116)	(9.40e-05)	(0.00116)
Firm Tech Diversity 3ys	-0.00536	-0.0111		
	(0.0299)	(0.0298)		
Firm Tech Diversity 5ys			-0.135**	0.0173
			(0.0616)	(0.0745)
Firm Age	0.00239	0.00304	0.00257	0.00299
	(0.00264)	(0.00276)	(0.00271)	(0.00277)
Firm Size	-4.67e-06*	-2.69e-06	-4.92e-06**	-2.58e-06
	(2.49e-06)	(2.43e-06)	(2.12e-06)	(2.40e-06)
VC Backed Firm	-0.0538**	-0.0667***	-0.0532**	-0.0654***
	(0.0244)	(0.0228)	(0.0229)	(0.0235)
Integrator	0.0356	0.0158	0.0214	0.0163
	(0.0303)	(0.0303)	(0.0303)	(0.0319)
Modular $Innovation_{t-1}$	0.496***	0.493***	0.494***	0.493***
	(0.0168)	(0.0172)	(0.0161)	(0.0174)
US	-0.0744***	-0.0642**	-0.0511**	-0.0633***
	(0.0258)	(0.0253)	(0.0235)	(0.0234)
Year Dummy	Included	Included	Included	Included
Constant	-0.466***	-0.490***	-0.475***	-0.502***
	(0.0438)	(0.0464)	(0.0319)	(0.0318)
Observations	409	409	409	409
Number of Firm	51	51	51	51

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 13. Results of Random-Effects Panel GEE Models with Negative Binomial Distribution Predicting Firm Architecture Innovation

VARIABLES	**Model 1** Architecture Innovation_t	**Model 2** Architecture Innovation_t	**Model 3** Architecture Innovation_t	**Model 4** Architecture Innovation_t	**Model 5** Architecture Innovation_t	**Model 6** Architecture Innovation_t
Level of Decomposability		-0.00171	0.225*		0.00277	0.418***
		(0.0312)	(0.128)		(0.0602)	(0.143)
Level of Decomposability Sq			-0.235*			-0.375***
			(0.137)			(0.131)
Firm Patent Stock	0.000227**	0.00118	0.000720	0.000244**	0.00116	0.000665
	(9.20e-05)	(0.00193)	(0.00191)	(0.000100)	(0.00196)	(0.00191)
Firm Tech Diversity 3ys	-0.0281	-0.0305	-0.0257			
	(0.0352)	(0.0333)	(0.0351)			
Firm Tech Diversity 5ys				-0.0321	-0.00397	-0.0934
				(0.0352)	(0.0700)	(0.0651)
Firm Age	-0.00159	-0.00150	-0.00166	-0.00150	-0.00155	-0.00151
	(0.00213)	(0.00205)	(0.00214)	(0.00208)	(0.00204)	(0.00214)
Firm Size	-7.97e-06***	-6.10e-06*	-5.90e-06*	-7.79e-06***	-5.65e-06*	-5.40e-06*
	(2.11e-06)	(3.26e-06)	(3.11e-06)	(2.10e-06)	(3.16e-06)	(2.98e-06)
VC Backed Firm	-0.0180	-0.0262	-0.0195	-0.0155	-0.0226	-0.0167
	(0.0324)	(0.0321)	(0.0298)	(0.0325)	(0.0319)	(0.0287)
Integrator	0.0274	0.0206	0.0220	0.0227	0.0191	0.0166
	(0.0296)	(0.0285)	(0.0272)	(0.0302)	(0.0295)	(0.0283)
Architecture Innovation_{t-1}	0.509***	0.512***	0.517***	0.507***	0.514***	0.516***
	(0.0214)	(0.0236)	(0.0227)	(0.0211)	(0.0221)	(0.0205)
US	-0.0334	-0.0350	-0.0317	-0.0224	-0.0276	-0.0203
	(0.0339)	(0.0329)	(0.0306)	(0.0337)	(0.0327)	(0.0304)
Year Dummy	0.00159	0.00150	0.00166	0.00150	0.00155	0.00151
	Included	Included	Included	Included	Included	Included
Constant	-0.405***	-0.432***	-0.443***	-0.436***	-0.473***	-0.474***
	(0.0772)	(0.0776)	(0.0748)	(0.0556)	(0.0546)	(0.0519)
Observations	402	402	402	402	402	402
Number of Firm	50	50	50	50	50	50

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 6. Entrants per Year and Total No. of Firm per Year in the Global LIB Industry

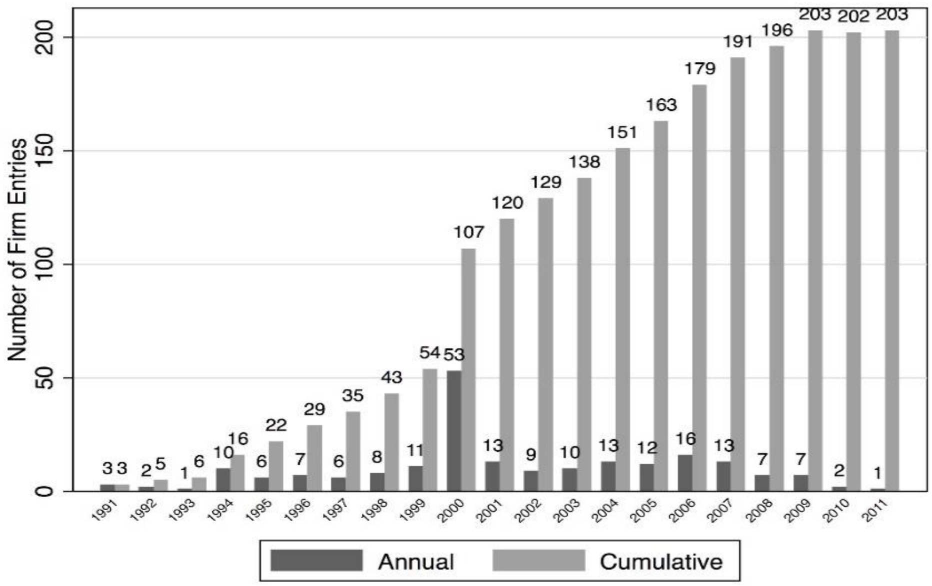
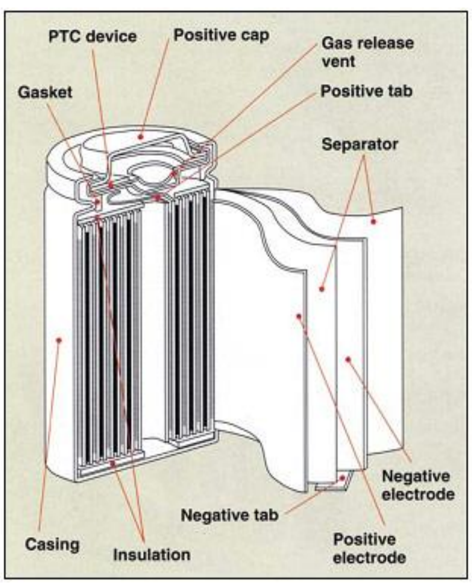
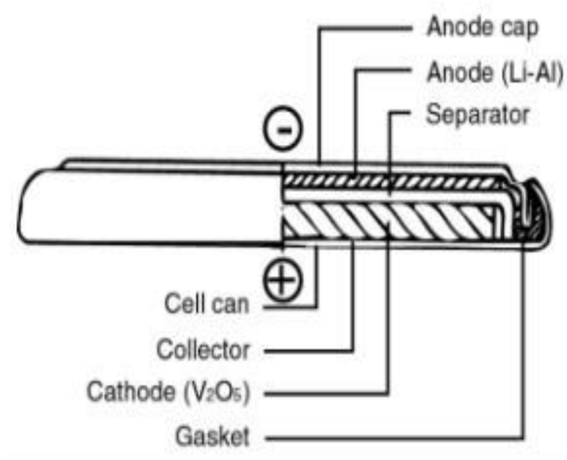


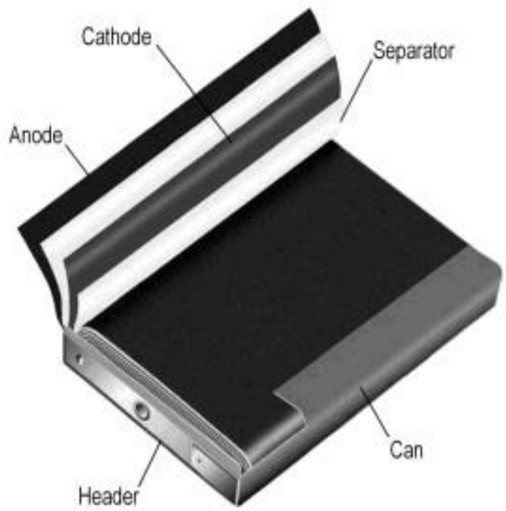
Figure 7. Types of LIB Cells





Cylinder Cell

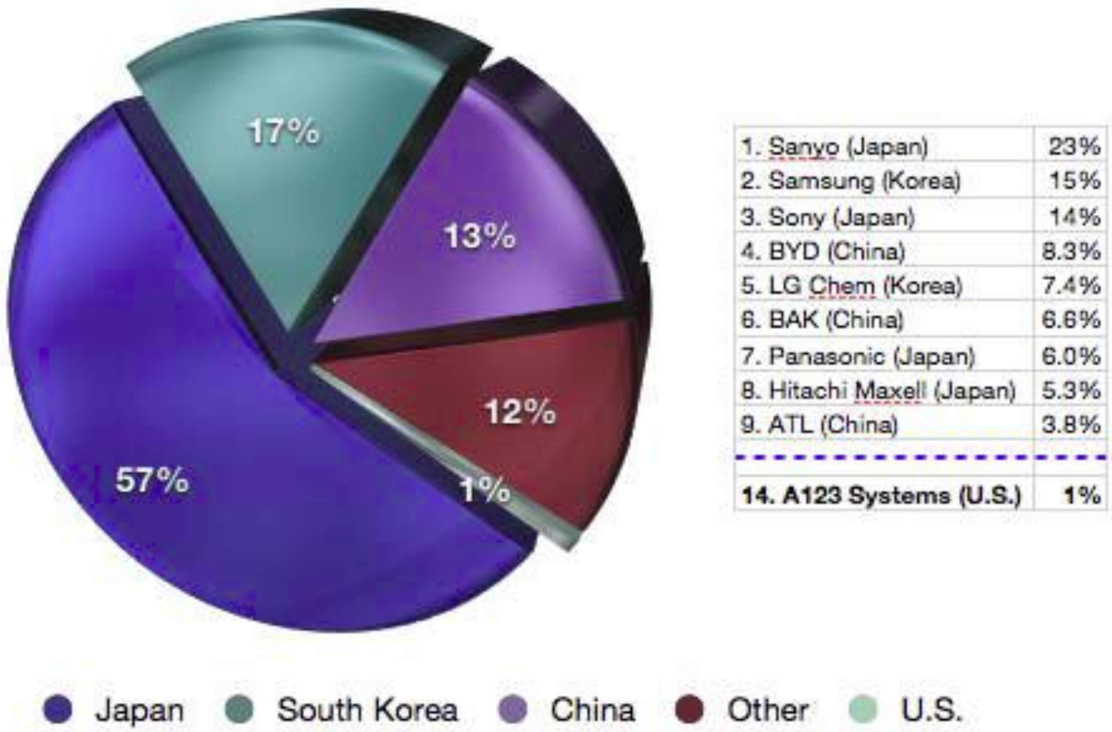
Button Cell



Prismatic Cell

Pouch Cell

Figure 8. Global Lithium-Ion Battery Market Share, by Country and by Firm. Source Center on Globalization, Governance & Competitiveness Based on (METI, 2010; NEDO, 2009)



CHAPTER 5

CONCLUSION

This chapter contains four sections: a summary of my three essays, theoretical contributions, empirical contributions, and limitations and openings for future research.

Summary of Three Essays

My dissertation answers the fundamental question of why new ventures make different strategic choices including 1) product market scope, 2) technology search scope, and 3) new product choices by examining internal firm factors, more specifically, individual and structural determinants. Integrating insights from several disciplines into the realm of strategic entrepreneurship, the dissertation poses significant but under-examined issues related to 3 new venture strategies in a nascent, technologically intensive industry. Using ideas from entrepreneurship on founder pre-experience, from evolutionary economics on search for new technological knowledge base, from network perspectives on knowledge structure, and from strategic decision-making, my dissertation provides empirical evidence that explains heterogeneity in new venture strategies.

My first essay investigates various types of founder pre-entry experience to unpack their impact on demand-side strategy. More specifically, this essay explores how different types of founder pre-entry experience affect the market scope of new ventures. The major finding of this study is that both relevant industry experience and prior founding experience foster market scope expansion, whereas diverse industry experience constrains market scope expansion. Furthermore, the positive effect of relevant industry experience is more pronounced than the effect of prior founding experience.

Meanwhile, my second essay investigates various types of founder pre-entry experience to unpack their impact on supply-side strategy. More specifically, this study examines how the various features of founder industry experience before entry into the focal industry affect two types of search strategies – breadth and depth. My findings indicate that new ventures with founders whose prior industry experience is 'relevant' to a focal industry are positively related to both breadth and depth search strategies, whereas new ventures with founders whose prior industry experience is 'diverse' are negatively related to both breadth and depth search strategies.

Turning my focus from individuals to structure, the third essay investigates the impact of a firm's knowledge structure on product commercialization strategy. More specifically, this study chooses one significant type of firm knowledge structure – knowledge decomposability – to explore its impact on two types of new product innovation – modular vs. architecture. I contend that the level of decomposability in a firm's knowledge network has differential effects depending on the type of product innovation. My analyses indicate that there is a positive relationship between the level of decomposability and a firm's modular innovation, whereas there is an inverted U-shape relationship between the level of decomposability and a firm's architecture innovation.

Theoretical Contribution

My dissertation sheds light on a key issue in entrepreneurship and strategy by theorizing on the origins of heterogeneity in new venture strategies. By unpacking the micro-foundations of various types of new venture strategies, my dissertation shows that internal firm-level factors are the main driver of firm-level outcomes (Felin and Foss, 2005). More specifically, my dissertation highlights that founders and the structures embedded in their shared beliefs are the locus of new venture strategies. Thus, by emphasizing the role of individual knowledge, my dissertation responds to an important call that research needs to look beyond organizational capabilities as the source of firm strategies.

The first essay reveals a number of key insights. First, this study has important implications for research on entrepreneurial decision making. So far, the extant research on entrepreneurship has focused on firms during their early years of operation and, thus, overlooks the critical role founder prior experience plays in forming the seed of a new venture's evolution and long-term prospects (Beckman, 2006, Shane, 2000; Shane and Khurana, 2003). To fill this gap, I explored the significant influence that founder pre-entry experience exerts on formulating the market scope trajectories of new ventures over time. Further, my study also contributes to entrepreneurship literature by investigating how founders' knowledge endowment shapes new firm performance (Brüderl et al, 1992; Carroll and Mosakowski, 1987; Shane and Stuart, 2002; Unger et al., 2011). The major shortcoming of this stream of research is the inconclusive evidence regarding the role that a founder's knowledge plays in affecting new venture outcomes, including survival (Brüderl et al, 1992) and sales (Delmar and Shane, 2006). One way to resolve this inconsistency is to consider the intermediate processes that founder characteristics affect, which then influence new venture performance later on. By investigating one of the key strategic choices new ventures make – market scope – my study shows how different types of knowledge endowment foster or constrain the market scope expansion of new ventures. Although my study cannot directly answer the question of which market scope strategies are more profitable, the unique assets derived from each type of founder experience may provide a clue. Founders who have relevant industry experience may be best positioned to choose more promising markets within a focal industry, as they have accumulated a tacit understanding of the industry's products, markets, and resources.

The study also contributes to the burgeoning literature of intra-industry diversification (Stern and Henderson, 2004; Li and Greenwood, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013), defined as new ventures' presence in more than one product line (Stern and Henderson, 2004) or operation in more than one market (Li and Greenwood, 2004) within a single industry.[5] Given the prevalence of this phenomenon in high-tech industries (Tanriverdi and Lee, 2008), research has begun to investigate the link between intra-industry diversification and performance (Zahavi and Lavie, 2013). By claiming that intra- and inter-industry diversification are fundamentally different, this stream of research largely examines the performance implications of intra-industry diversification (Wu, 2013; Zahavi and Lavie, 2013). Still missing in this conversation, however, is theorizing on the antecedents of intra-industry diversification. Given that new ventures and established firms are inherently different entities, we need to separately scrutinize factors that affect the market scope of new ventures. To respond to this call, recent studies have begun to look into how environmental factors affect the degree of market scope expansion within a single industry (Wu, 2013; Gambardella and Giarratana, 2013). However, by recognizing the fact that the lack of experiential knowledge within a

[5] Although the concept of firms' market scope, which is characterized by the range of customer segments firms are positioned to target, is subtly different from within-industry product diversity, defined as the degree of variation in a firm's portfolio of related products in a particular industry (Stern and Henderson, 2004) , I use them interchangeably in the study.

focal industry leads new ventures to draw resources and capabilities mainly from founders, my study complements the literature by shedding light on the internal firm factors that affect market scope. By showing that founder knowledge endowment is a basis for firm capabilities that are then related to market scope decisions (Døving and Gooderham, 2008), my study proposes that founders have a paramount impact on the market scope choices of their new ventures.

Furthermore, my research provides important insights into evolutionary economics. Thus far, extant research on evolutionary economics has examined either how pre-entry experience shapes new ventures' initial strategies (Helfat and Lieberman, 2002; Helfat and Raubitschek, 2000) or it has delved into the relationship between pre-entry experience and firm performance (Agarwal et al, 2004; Klepper, 2002; Wenting, 2008; Simons and Roberts, 2008, Chatterji, 2009). The literature therefore leaves the effect of pre-entry experience on post-entry strategies, including the evolution of market and technological choices, within a black box. By furthering inquiries into the effect of pre-entry experience on post-entry strategic choices, my study fills significant gaps in the study of evolutionary economics.

The second essay also provides a number of key insights for literature on technological search, entrepreneurship, and industry evolution. First, the study contributes to technological search literature, as it begins to investigate individual-level determinants of heterogeneity in the technology search strategies of new ventures, which is an under-explored area. Although it is essential to examine the antecedents of firms' various search strategies in order to understand the whole process of what determines strategic choices and how such different choices affect innovative performance, the literature thus far has mainly focused on the performance implications of search strategies (Katila and Ahuja, 2002; Laursen and Salter, 2006; Keupp, Palmie, and Gassmann, 2011; Terjesen and Patel, 2015). My study fills this gap in the technological search literature.

In addition, this study has important implications for research on entrepreneurial decision-making. So far, entrepreneurship research has focused on firms during their early years of operation, and thus likely overlooks the critical role founder prior experience plays in forming the seeds of a new venture's evolution and long-term prospects (Beckman, 2006, Shane, 2000; Shane and Khurana, 2003). I explore the significant influence founder pre-entry experience exerts on formulating the search trajectories of new ventures.

Meanwhile, my third study advances the literature by responding to calls that 1) research needs to explore whether the structure of a firm's knowledge network accounts for differences in firm innovation (Wang et al, 2014), and 2) innovation literature will be advanced by examining how the structural features of a firm' knowledge base distinctively affect various types of firm innovation (Guan and Liu, 2016). This study provides further understanding about how and why the structural properties of a focal firm's knowledge network influence the type of product innovation.

The study also contributes to literature on product architecture. While product architecture research has examined several aspects of firm innovation (Murmann *et al.*, 2006), this stream of literature has less paid attention to the role of knowledge structure on product innovation. By showing that the degree to which components are linked to other components in the technological system varies depending on the significance of each knowledge component (Tushman *et al.*, 1998), this study confirms that the structural features of knowledge networks need to be fully understood as one of key factors in determining firm product architecture, which leads to firm innovation.

Empirical Contribution

My dissertation also provides several empirical contributions. In the first essay, I use a yearly count of markets where new ventures enter, unlike many studies that either use a dichotomous variable capturing whether or not market scope change was made after founding, or rely on respondents' memories to provide self-reported data on market scope change. Moreover, by collecting specific technological information on products and the critical dimensions that founders consider when deciding their product market scope – in this case the choice of cathode material – my study precisely captures changes in product markets over time.

In both the first and second essays, I enrich evolutionary economics by decomposing coarse firm-level data on pre-entry capabilities into the delicate details of founder-level prior experience (Qian et al, 2012; Kapoor and Furr, 2015). Research on industry evolution has largely measured pre-entry experience as a dichotomous, firm-level variable (i.e., diversifying entrants versus start-ups), even though the literature acknowledges the fact that start-ups may benefit from their founder's pre-entry experience (Agarwal et al.2004, Helfat and Lieberman 2002, Klepper 2002). By collecting the detailed career trajectories of founders, my study captures the rich heterogeneity in the types of experience new ventures bring into an emerging industry.

In addition, a critical empirical gap emerges from the fact that as patents are the fundamental knowledge through which new products have been developed, patents are insufficient as a tool of measurement in this type of innovation study. In order to capture firm innovation, the utilization of a firm's product information is more appropriate; thus, my third study fills empirical gaps in measuring firm innovation by using product-level data instead of patent-level data.

Limitations and Future Research

I am cognizant of the limitations of my essays. First, my research is based on an industry that is approaching maturity but has not yet arrived at the shake-out stage. Ideally, an examination of my theoretical predictions through the entire life of an industry would make for a more complete story, thus increasing the power of generalizability. Replicating this study in other industries would be one promising venue for future research.

Although the single industry setting as well as the random effects model allowed me to control for the many unobserved factors that may influence the search process, my findings are still subject to unobserved heterogeneity. For example, unobserved factors such as behavioral and personality characteristics unique to different founders may play a role in their decisions to broaden or deepen the knowledge bases of their new ventures. Incorporating founders' behavioral patterns, such as their degree of risk aversion and their personality, into this vein of research would further enrich the literature.

Although my findings indirectly answer the question of which new venture strategies are more desirable for good performance later on, my dissertation does not paint the whole picture of the determinants and consequences of new venture market scope trajectories. Thus, it is still unclear whether and how founder knowledge endowment can enhance new ventures' survival likelihood through choices on market and technological scope. My next study will unpack how the genesis of market scope choices can enhance or hamper the chances of firm survival. Through a rich data set in which I have collected detailed information on the exact time of market scope expansion events during the life cycle of new ventures, I can rule out the possibility of simultaneity in the relationship between market scope and new firm survival.

Founder origin also needs to be studied more specifically. Although I tracked founders' working trajectories before entry into the LIB industry, the operationalization of founder relevant industry experience can be detailed further. From the sample, relevant industry experience incorporates both experience from upstream industries (i.e. electrical engineering, chemical industries) and downstream industries (i.e. battery, energy industries). Given that the content and scope of the knowledge gleaned from upstream and downstream industry experiences is quite different, further studies could look into the distinctive impact of different types of founder relevant industry experience on the search strategies of new ventures.

In the third essay, a firm's knowledge base can display various structural patterns including cohesiveness, small-world, centralization, or hierarchical (Rivkin *et al.*, 2007).

An investigation of how these structural patterns tie all the knowledge components within a firm together and affect the types of firm innovation is another fruitful research area.

Lastly, another concern in this study is that the number of observations has shrunk drastically after merging the knowledge network data and LIB product data. As an extension, a future study will include two additional major battery technologies – lead-acid and nickel-based – by collecting patents and product data. As all three technologies are comparable in their product architecture while also presenting sufficient variation in terms of materials, main components, and system design, the rechargeable battery industry is the ideal place to investigate the role of knowledge structure in the development paths of new battery products.

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