ARCHITECTURAL EVOLUTION OF NASCENT INDUSTRIES:
EVIDENCE FROM SOLID-STATE LIGHTING

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ABSTRACT

My dissertation is a study of firms' strategic differences and the performance consequences of these differences in nascent industries. I relax the implicit assumption in the existing literature that a technological breakthrough is exogenous, and provide theoretical and empirical accounts of knowledge evolution before a new technology gets commercialized. In Chapter 2, I highlight the evolution of a technology at the industry level and argue that there exists a pre-commercialization technology *life cycle*. I develop a series of propositions related to the technology's architectural evolution during the pre-commercialization phase, and show that an emerging architecture becomes fully integrated before the inception of a new market. In Chapter 3, I shift the focus to the firm level, and compare the pre-commercialization search strategies of market incumbents facing a technological obsolescence to those of technology incumbents disrupting an existing market. I show that these two groups of incumbent firms invest heavily in an emerging technology even before the market takes shape, and that they engage in different search strategies, specifically in the degree to which they integrate or modularize the knowledge about individual technology components across two stages of a pre-commercialization life cycle. In Chapter 4, I argue that such pre-commercialization strategies have post-commercialization consequences. This dynamic view suggests that a select group of established organizations enter a new product market and the heterogeneity in their pre-entry experiences has direct consequences for the product's initial performance. Throughout, this study uses the emergence of the solid-state lighting (SSL) market as an empirical context.

DEDICATION

This dissertation is dedicated to my advisor, Dr. MB Sarkar, whom heaven called upon a week after my oral defense, and who shines in every word of this dissertation.

Your First Doctoral Student, Alice

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

In my dissertation, I study the evolution of a technology architecture in a nascent industry, using the emergence of the solid-state lighting industry as my empirical context. Strategy research emphasizes our understanding of firms' strategic differences and their possible performance consequences. In this respect, an evolutionary perspective is crucial for explaining the mechanisms by which firm-level differences develop (Barnett and Burgelman, 1996). Industry evolution studies usually take off from the birth of a nascent product market. That is, taking for granted the arrival of a technological breakthrough, studies then explain the industry's evolution as a new product gets commercialized in a new market (Gort and Klepper, 1982). This stance, however, prevents us from understanding two critical mechanisms by which industries and firm strategies evolve. First, a new technology—be it radical, competence-destroying, or disruptive (Christensen, 1997; Tushman and Anderson, 1986)—does not come about exogenously. Instead, such "discontinuity," which can potentially lead to the creation of a new market, is the result of an accumulative process of inventive efforts in diverse technology fields, a phenomenon that is only traceable during the pre-commercialization period. I therefore provide theoretical and empirical accounts of how a new technology gets developed from multiple, converging fields of science in the anticipation of a new market. Moreover, I show that there is in fact "life before a life cycle," and that the pre-commercialization period is marked by two stages of a technology's architectural evolution.

A second limitation prevalent in the literature is a lack of understanding of how firms carve out their pre-(market) entry experiences. The literature focuses on the entry patterns by different types of firms, most conspicuously comparing those by *de alios* to *de novos*, and makes predictions about their performance *post* market-formation (e.g., Agarwal, Sarkar, and Echambadi, 2002). Yet we have limited evidence of how *de alio* firms, which have an organizational history before the new market opens, develop (or do not develop) the capabilities to perform in a new technological environment. In this dissertation, I thus provide a direct investigation into established firms' pre-commercialization experiences and make predictions about how these experiences affect their post-entry performance.

First, I investigate the pattern of knowledge evolution at the industry level. I focus on the evolution of a technology architecture during the pre-commercialization phase and show that there is a pre-commercialization life cycle that is distinct from the post-commercialization life cycle. Using the patents representing the inorganic light-emitting diode (LED) technology that makes up solid-state lighting, I find that an emerging technology system becomes more integrated over time, in terms of both depth and breadth of interdependence across the knowledge underlying individual components of its emerging technology architecture. Interestingly, this is the opposite pattern from the well-understood one of a post-commercialization life cycle moving towards increasing modularity. I present empirical evidence that the pre-commercialization technology life cycle unfolds in two distinct phases: the era of modularity and the era of integration, where the latter phase arrives after the interdependence across all the components in a system spans the entire architecture.

Next, I move to studying the search strategies of incumbent firms along the life cycle theorized at the technology system level. In Chapter 3, I discuss two types of established organizations that invested in emerging solid-state lighting technology: market incumbents facing technological obsolescence and technology incumbents that possess the focal technology that causes “creative destruction” in an existing market. Recent studies show that although incumbent organizations face innovation challenges relative to new firms due to inertia, they are not completely oblivious to an emerging technology that can potentially shake their existing capabilities and complementary assets. Rather, market incumbents do invest in emerging technology fields, and they do so during the pre-commercialization period. I study and compare the search strategies of market versus technology incumbents in the anticipation of a new industry. In my empirical setting, market incumbents are lighting firms that are masters of Edison’s light bulbs, and technology incumbents are semiconductor firms that possess the core technological capability of developing the semiconductor-based LED lighting. The findings in this chapter show that as two groups of established organizations journey across the pre-commercialization period, lighting (semiconductor) firms engage in less (more) integrative search after the advent of high brightness blue LEDs, which the literature would usually mark as a “technological breakthrough” or “technological discontinuity.”

In Chapter 4, I study the effect of pre-commercialization technological searches on initial post-commercialization performance of firms that enter into a new solid-state lighting industry. Specifically, I focus on the effect of knowledge integration, or the extent to which firms integrate knowledge about different LED components, on firms' product performance in the early years of a new solid-state lighting market. Taking into account a potential selection issue related to the unobserved heterogeneity that could systematically affect a select group of firms making market entries, I find that pre-commercialization knowledge integration helps firms launch higher quality lighting products. However, the extent to which it helps differs by the type of entrant: vertical and horizontal entrants gain different benefits. I find that in terms of making better quality of light, the benefits of knowledge integration are more pronounced for vertical entrants that previously lacked integrative capabilities (Helfat and Raubitschek, 2000) than for horizontal entrants. I hence argue that if the vertical entrants develop the integrative knowledge of a system of technology components before the inception of a new market, they can produce higher quality products than those who modularize the knowledge, given that they have entered the market.

Using the phenomenon of the emergence of the solid-state lighting industry both at the technology and firm levels, my dissertation contributes to the literature of industry emergence by examining the interplay between architectural evolution and firm strategy. I show that a new technology journeys across two distinct phases of a pre-commercialization life cycle. At the backdrop of this life cycle, established organizations engage in idiosyncratic search strategies before entering into a nascent market. I finally contend that studying the pre-commercialization evolution of a technology is necessary in order for us to more fully understand firms' post-commercialization performance outcomes. Below, I give an overview of the solid-state lighting industry, which my following three chapters employ as an empirical context.

Empirical Setting: Solid-State Lighting (SSL) Industry

I use the emergence of the solid-state lighting industry as my empirical context. Solid-state lighting consists of two technologies: the inorganic semiconductor-based light-emitting diode (LED), and the organic polymeric-based light-emitting diode (OLED). While both technologies are the subject of active research worldwide, the focus of this dissertation is the use of high-brightness inorganic LEDs in applications that come under a broad definition of lighting, the phenomenon generally described as *solid-state lighting*. With the promise of being more than ten times as efficient as incandescent lighting, LEDs strive to replace Edison's light bulb, now more than a century old. An LED is a semiconductor light source, and alone it cannot be used for general illumination. It needs additional components to create a lighting system, including electrical, thermal, and optical components.

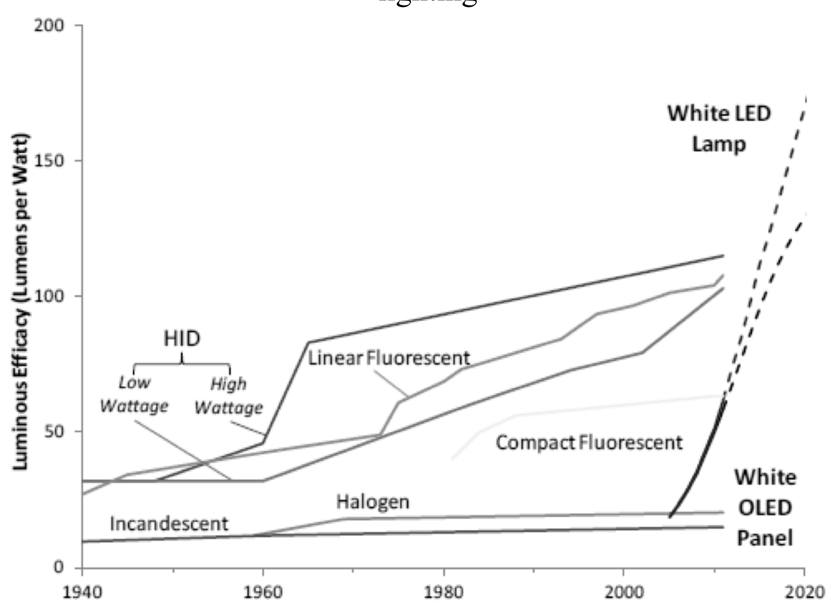
The LED industry has gone through several development stages since the first LED was invented in 1962. Red, green, and yellow LEDs have been available since then, enabling their application in signage, traffic lights and entertainment lighting; however, the advent of high-brightness blue LEDs based on GaN (gallium nitride), invented by three Japanese scientists, including Shuji Nakamura, at Nichia in 1993, made a high-efficiency white light source possible.[1] Because an LED is a monochromatic light source (i.e., blue LEDs emit blue light), white light is achieved by combining the emissions of red, green, and blue (RGB) LEDs or by using phosphor conversion, in which a yellow phosphor is used on or near the LED to convert the blue light into white light. The second, phosphor technology, is the more common. For the last four decades, LED technology has made remarkable advances in terms both of LED device performance and of color availability across the visible spectrum. Light output measured in LED flux per package has doubled every 18 to 24 months over the last three decades (StrategiesUnlimited, 2002). This trend is famously referred to as “Haitz’s Law,” after the former Agilent Technologies Semiconductor Group R&D Manager Roland Haitz in the LED industry. In parallel, the progress in white lighting efficacy shown in Figure 1 (page 7) has reached about 150 lumens per watt (lm/w) for commercial lamps, putting it at a level to compete with incumbent lighting products.

I have identified the pre-commercialization period of the solid-state lighting industry as the years preceding 2007, when the high-efficiency and high-power LED lighting fixture and bulb were introduced in market (Ledbetter, 2014).[2] LED-based lighting products come in two forms: replacement lamps that can be retrofitted into, one-for-one, the incumbent lamp (i.e., incandescent and fluorescent socket bulbs) without changing the original fixture, and luminaires, which require replacement of the

[1] Isamu Akasaki and Hiroshi Amano, at Nagoya University, and Shuji Nakamura, at UC Santa Barbara, were rewarded the Nobel Prize in Physics for inventing the high-brightness blue LEDs in 2014 (Nobelprize.org).
[2] The LR6 downlight (a retrofit kit) from LED Lighting Fixtures (later bought by Cree), in 2007. The Lighting Science Group LED bulb (first bulb with over 300 lumens output), in 2007.

incumbent fixture. Depending on usage, LED lighting applications can be either residential or industrial.

Figure 1.1 Historical and predicted lighting efficacy of white LED and incumbent lighting



Source: Department of Energy, 2012. Multi-year program plan. p. 38.

Note: The figure plots the most popular performance metric of lighting (lumen/watt) for various lighting technologies over time. It shows that it is only very recently that the performance of white LED lighting has caught up with incumbent technologies.

CHAPTER 2

THE ARCHITECTURAL EVOLUTION OF TECHNOLOGY: A PRE-COMMERCIALIZATION PERSPECTIVE

Introduction

How does technology evolve as a new industry emerges? An evolutionary model of technological changes proposes that technology goes through stages of development along with related product life cycles (Abernathy and Utterback, 1978; Anderson and Tushman, 1990; Nelson and Winter, 2002; Suarez and Utterback, 1995; Tushman and Anderson, 1986). The literature usually begins by identifying a technological breakthrough that triggers a variation in product classes, and argues that incremental innovation takes over after dominant designs emerge. The era of incremental change continues until another technological discontinuity arrives (Anderson and Tushman, 1990; Suarez and Utterback, 1995). Such incessant cycles of product and technology development underlie industry emergence and evolution.

Despite the well-documented co-evolutionary cycle of products and related technologies in an industry (e.g., Gort and Klepper, 1982; Helfat and Raubitschek, 2000), what is still left for discussion is how technologies underlying a new product evolve *irrespective* of their market outcome. More specifically, we do not have a good understanding of how new technologies evolve to become a "breakthrough" or "discontinuity" that triggers a new industry (or subfield) inception. Scholars, especially historians of technology, in this line highlight that products and technologies in fact undergo different evolutionary dynamics (e.g., Brusoni, Prencipe, and Pavitt, 2001;

Pavitt, 1998; Rosenberg, 1969; Rosenberg, 1982). In a seminar paper, Gort and Klepper (1982) also point to two steps of new product innovation: the first step is the technical development of a new product, and the second step focuses on introducing that product into the new market. Much of the prior literature has focused on the latter step; it suggests that a new technology life cycle begins with the initiation of a new product market, thus assuming that nascent industries have very little industry-specific knowledge (1982). This study, however, directs scholarly attention back to the first, much neglected step of product innovation, namely technical development. In order to focus on technology development, I first relax the exogeneity assumption of "technological breakthrough" in the literature, which defines the point of punctuated equilibrium (Tushman and Anderson, 1986), and delve into the relatively less understood period of pre-commercialization, or the period before the breakthrough brings about a new industry. I hence examine the "life before a life cycle."

The second approach of this study derives from the theoretical and empirical notion that a product contains multiple component technologies (Arora, Fosfuri, and Gambardella, 2001; Brusoni, Prencipe, and Pavitt, 2001; Gambardella and Torrisi, 1998; Granstrand and Sjölander, 1990). I conceptualize the technology as a *system* composed of multiple subsystems and components nested in hierarchy (Simon, 1962). An emerging technology system will show a pattern of interdependence among the bodies of knowledge underlying the technology subsystems and the components within a system, which together form a new product innovation (Baldwin and Clark, 2000; Murmann and

Frenken, 2006; Pavitt, 1998; Schilling, 2000; Simon, 1962). I refer to this pattern of interdependence as *technology architecture.*

I propose an evolutionary model of the technology architecture of nascent industries, in which multiple technology subsystems and components move through their respective life cycles, while the patterns of interactions also evolve. I use the phenomenon of the emergence of the solid-state lighting industry as the empirical context to explore whether there exists a distinct pre-commercialization life cycle, by focusing on the technical development of the inorganic light emitting diode (LED) technology. The LED presents a compelling example for studying technology evolution for two reasons. First, it has undergone several decades of technical development in the hopes of bringing the white LED light revolution into reality and replacing Edison's century-old light bulb. This allows for an elongated period of pre-commercialization, in which I can observe long-sought technological exploration before product commercialization. Second, the LED light necessitates multiple technology components to work together to enable general illumination. That is, designing the right interface between various technological components is crucial for light performance, a critical condition for my examination of the interdependence across technology components. Consequently, I have built a unique patent database of 30,840 US granted patents filed by 3,861 unique entities (i.e., universities, government organizations, individuals and for-profit firms) during the pre-commercialization period (1981-2006), which holistically represents the LED technology system. Also, in order to capture the technology architecture, I adapted the principle and technique of the Design Structure Matrix, which allowed me to track an intricate pattern of interdependence between system components, and to effectively visualize the system architecture. I identified the dependence structure across LED components from which I theorize about an architectural evolution during the pre-commercialization period. As a result, I find that it exhibits features distinct from those of the post-commercialization period.

This study underscores three key findings about the evolution of technology in emerging industries. First, I find that there is "life before life cycle." By extending the timeframe to the pre-commercialization period, I show that an industry goes through an accumulative process of technical development before "discontinuity" arrives. I find that a technology's life cycle unfolds as multiple technology components exhibit their respective life cycles over time. Technical development begins with a radical innovation in the core technology (in this study, the LED light source), followed by innovations in complementary technologies such as optical and thermal controls at varying growth rates. Innovation efforts in the core technology (measured by the number of patents filed) show a remarkable growth rate during the pre-commercialization period, but begin to taper once products have hit the market. Interestingly, the converse is true for complementary technologies. This implies that the implicit treatment, in the prior literature, of an emerging technology as a single-layered invention can obscure the multiplicity of the phenomenon of a technology's emergence. And what seems like a discontinuity at an aggregate level can instead be smooth, developmental trails of technological invention at the component level. As in the case of an LED, a "nascent" industry has already deposited the abundant knowledge in the core technology around the time products are launched in a new market. This finding is in contrast to the received wisdom that new industries know very little about an incoming technology.

The second important finding of this study is that during the pre-commercialization phase, a technology system becomes more integrated over time, as represented by the increase in the interdependence level across technology components within the system. This pattern is in contrast to the pattern of the post-commercialization phase, during which technology moves towards increasing modularity as uncertainty is resolved over time (Abernathy and Utterback, 1978; Baldwin and Clark, 2000; Monteverde, 1995; Weigelt and Sarkar, 2012).

Lastly, I argue that a pre-commercialization technology life cycle can be divided into two different phases representing the respective characteristics of an evolving technology architecture: "*the era of modularity*" and *"the era of integration."* I uncover the underlying mechanisms of the pre-commercialization architectural integration by investigating its evolution at the component level. I find that the era of integration arrives only after the interactions across all the technology components span the entire architecture of a system. This suggests that a new industry undergoes a shift in the locus of innovation from technologies that represent independent, component knowledge to those that connect groups of knowledge. And this architectural evolution takes place before products are first commercialized.

I make important contributions to the industry evolution literature by providing rich insights into how technological knowledge evolves as a new industry emerges. Specifically, I uncover the accumulative process of technical development underlying new product innovation during the pre-commercialization phase and illustrate that there is a "life before life cycle." By introducing the distinct pre-commercialization life cycle, this study opens a venue for future research opportunities that can systematically examine various endogenous factors leading to industry emergence. Also, I advance life cycle studies by focusing on the evolution of technology architecture. In so doing, I bridge the insights from the modularity (Baldwin and Clark, 2000; Simon, 1962) and the industry evolution literature (e.g., Gort and Klepper, 1982; Nelson and Winter, 1982; Tushman and Anderson, 1990) to underscore the evolving dependence structure of knowledge elements in an emerging industry. The findings show that the pre-commercialization technology life cycle undergoes an architectural shift, after which all the technology components become dependent upon each other. This suggests that the *linkages* between technology components have been already revealed and are not "new to the world" by the time products are first commercialized. Lastly, I introduce the Design Structure Matrix to represent the citation patterns of patents for the first time, to my knowledge. This new network analysis tool will advance our understanding of the knowledge structure of any system (Fleming, 2001; Yayavaram and Ahuja, 2008) by allowing us to see it in a more granular manner.

Technology Evolution *Pre* Commercialization

An evolutionary model of technological changes illustrates the temporal unfolding of the life of a new technology, which triggers new product introductions that in turn form an incessant chain of life cycles. A natural assumption in the literature is that nascent industries have little industry-specific knowledge, and hence a high degree of uncertainty in both technology and market during the era of ferment (Anderson and Tushman, 1990). The research thus begins by identifying a technological invention that brings about a new product generation (Anderson and Tushman, 1990; Christensen, 1997) and then documents an industry life cycle from the first incidence of product commercialization (e.g., Gort and Klepper, 1982; Agarwal and Bayus, 2002). Then, with hindsight, we map the life cycle of a new technology that is related to a new product class.

Yet the classic literature notes that "a product innovation is composed of two steps: the technical development of a new product and the introduction of the new product into the market" (Gort and Klepper, 1982: 630). While this theoretical foothold suggests that a separate evolution of technical knowledge may unfold *regardless of the market outcome*, the bulk of research spends the lion's share of its attention on the latter step, focusing on the dynamics *post*-commercialization. I intend to bring scholarly attention back to the first, much neglected step, focusing on the pattern of technology evolution. I therefore will not artificially truncate the examining period from the instance of a market formation, but will instead relax the exogeneity assumption of a technological invention that may or may not lead to successful product innovations. Investigating into the pre-commercialization phase, going beyond the identification of a technological invention that signals a new market application, provides empirical evidence of the accumulative process of technical development before the "discontinuity" arrives (Kuhn, 2012; Rosenberg, 1982). I build insights from the existing literature on technological change that “neither technologies nor the products that embody them emerge full-blown, all at once” (Baldwin & Clark, 2000: 2) and that this adaptive process also evolves, and what results is “the cumulative result of small changes” (3).

Studies of technology life cycles during the post-commercialization period give little evidence of how technological knowledge evolves during the pre-commercialization period. The reason is that the evolutionary process during the post-commercialization period necessitates incorporating ideas of sociocultural evolution (Anderson and Tushman, 1990; Campbell, 1965; Sahal, 1981; Suarez, Grodal and Gotsopoulos, 2015), so much so that the normal progress of technology is conflated with other drivers of innovation. Moreover, often an economic factor such as price is so wide-spread that it alone cannot explain the direction of technological changes (Rosenberg, 1969). Scholars of modular theories argue that products and processes become modularized towards the mature stages of an industry in order to better serve the heterogeneous needs of users, and that accordingly the division of labor becomes conspicuous (Baldwin and Clark, 2000; Langlois, 2003; Schilling, 2000). The question of whether the pre-commercialization period evolves towards modularization or integration of knowledge and processes is still unknown.

Technology as a System

Displacement of an old with a new technology is the hallmark of an industry emergence phenomenon (e.g., Adner and Kapoor, 2015; Tushman and Anderson, 1986). The exogenous treatment of the arrival of a new, displacing technology at the aggregate level, however, masks the accumulative inventive activities in multiple related technology domains. To the extent that the strategy literature has considered the pattern of technological changes, it predominantly describes them as single-layered inventions making a way into new market applications and evolving. The scrutiny of the development of complementary technologies is often delayed until the discussion of the emergence of a dominant design.

In fact, this simplistic view, which focuses solely on the core technology, effaces the fact that innovation entails inventive efforts undertaken in diverse technology subcomponents (Baldwin and Clark, 2000; Fleming and Sorenson, 2001; Simon, 1962). More importantly, it ignores the recombinative activity or system-level integration of related technologies that together enable product innovation (Fleming, 2001; Hargadon and Douglas, 2001; Jiang, Tan, and Thursby, 2011). Product innovations often incur a system-level challenge necessitating changes in the technology components and/or linkages underlying a new product class (Henderson and Clark, 1990). In this regard, we need an understanding of the pattern of intricate interdependence among the different kinds of knowledge underlying the different technology subsystems that together form an emerging invention. I thus view technology as a complex adaptive *system* of nested subsystems and components that interact together to exhibit the pattern of a dependency structure, defined as *technology architecture* in this study (Baldwin and Clark, 2000; Fleming and Sorenson, 2001; Simon, 1962). This definition highlights the two key features of a complex system. First, a system is composed of *multiple* subsystems and components nested in hierarchy. Hence, when technology evolution is viewed from the systems perspective, the underlying mechanisms will involve different patterns of changes that occur at different layers (Murmann and Frenken, 2006). Second, subsystems and components are to some degree interdependent and form an architecture of complexity (modularity) over time (Simon, 1962). When a technology system emerges, the knowledge flows across different subsystems and components, the pattern analogous to that of materials moving downstream in product value chains. Yet a difference is that the knowledge need not always come downstream, nor move upstream, and hence directionality has much more significant bearings on the theory of technology evolution. I borrow insights from modularity literature to look inside the evolving technology architecture of a nascent industry (Baldwin and Clark, 2000; Schilling, 2000; Sosa *et al.*, 2005). An architectural property can be described in terms of some degree of modularity, where a highly modular architecture is exemplified by an increased level of integration within the same module and near independence across the different modules (Baldwin & Clark, 2000; Schilling, 2000; Simon, 1962; Yayavaram and Ahuja, 2008). On the other hand, an integrated system has a high level of interdependence across its different modules. In the latter case, changing one component without affecting another system component becomes nearly impossible (Simon, 1962).

Studies show that technological change unfolds in an interdependent manner (Dosi, 1982; Pavitt, 1998; Rosenberg, 1969, 1982). Exploring the structure of dependence of a technology's components over time therefore enables me to understand the mechanisms of the technology's evolution during the pre-commercialization period. In the post-commercialization period, a technology architecture moves towards increasing modularity as a standard interface is established and uncertainty subsides (Abernathy and

Utterback, 1978; Baldwin and Clark, 2000). The pre-commercialization period is, however, absent of demand heterogeneity, which often acts as a factor forcing systems to move towards increasing product modularity (Schilling, 2000). In the pre-commercialization period, how do different technology components interact, in what pattern? Will these interactions become more prevalent over time? Where in the technology architecture does modularization or integration occur? In the following sections, I provide empirical evidence that offers answers to these questions.

Data

In order to study the process of architectural evolution in the context of industry emergence, I rely on patent data as indicative of the technological knowledge underlying new product innovation. Given the nascent stage of the LED industry, data collection has posed several challenges. My data collection effort spanned an 18-month period, during which I attended several industry conferences and sampled the LED patent data on the advice of industry experts. For the purpose of my study, I needed to collect the patents that represent each of the component knowledge in the LED system. [3] In this regard, I started with the proprietary LED patent database, LED PatentEdge, from an IP analytics firm, IP Checkups (www.ipcheckups.com). I chose this database because it was built with

[3] Searching by patent classes through USPTO for instance did not work effectively for the purpose of my study because it was challenging to extract LED-specific technologies related to general illumination. For example, USPTO class number 362, subclass 23.07, only represents illuminated indicators having the LEDs while

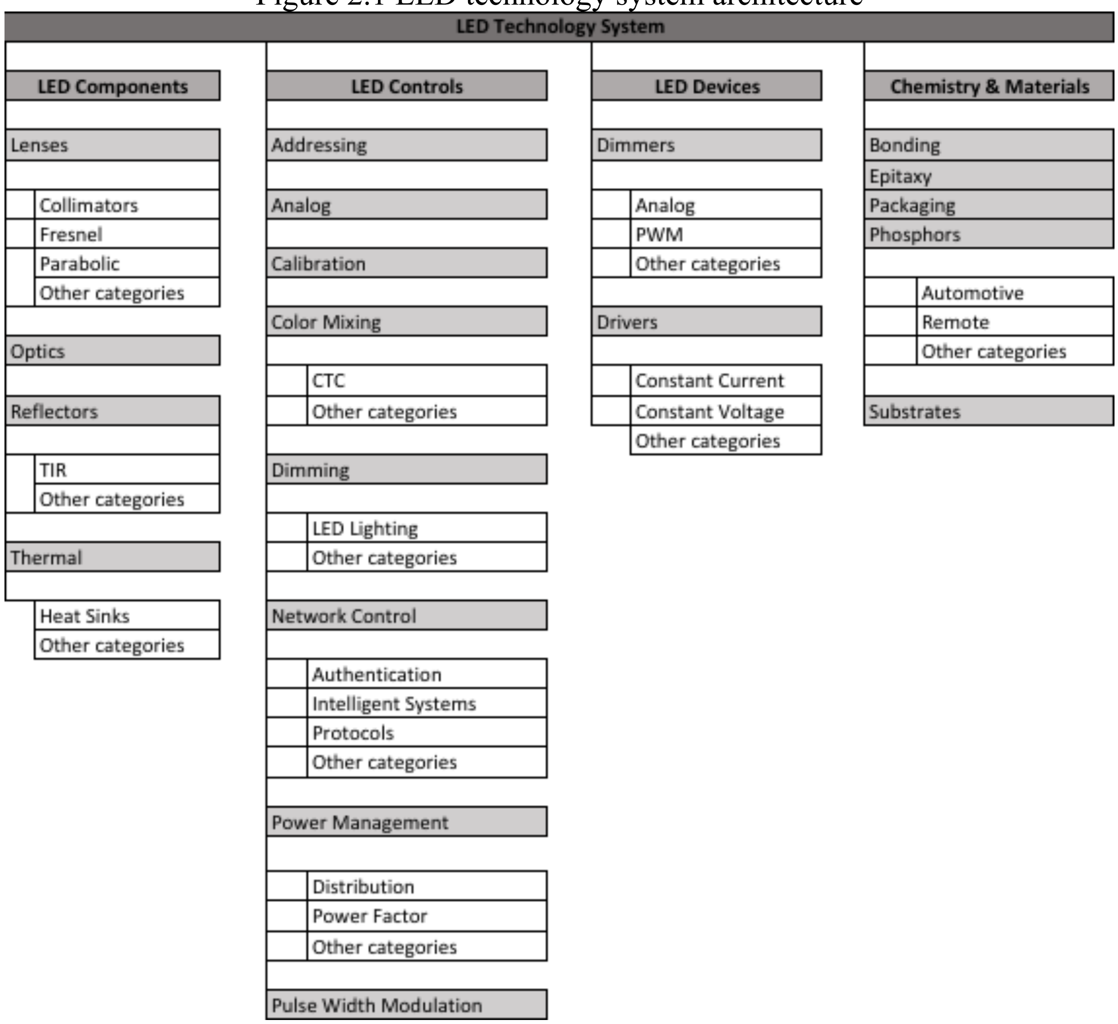
the expert text search algorithm underlying various LED technology components,[4] which became the major source of the representation of the LED system architecture in this study. Next, working closely with IP Checkups, I expanded its initial dataset to include forward and backward citations, which in this dissertation are conceptualized as the interdependence between various LED technology components. Third, I harmonized the assignee names using fuzzy matching algorithms in STATA 11.0 and manual matching.[5] Finally, I merged this patent dataset with data from Derwent Innovation Index to clear the assignee data further.[6] As a result, I have a final sample of 30,840 US granted patents filed by 3,861 unique entities (i.e., universities, government organizations, and for-profit firms aggregated to the parent firm) during the pre-commercialization period, 1981-2006.

LED system architecture: Through an iterative process using the above original patent dataset, and running validity checks of its categories with various trade journals including LEDs Magazine and LED professional and first-hand interviews with industry experts from several leading LED companies like Philips Lighting, I represent the LED technology system architecture as nested in 4 subsystems, 19 components and 37 subcomponents, as shown in Figure 2.1. Four subsystems represent Chemistry and Materials (16,811 patents), which forms “the core LED technology subsystem”, LED Components (5,376 patents), which house optical and thermal components, LED Controls (4,063 patents), which house light controlling components, and LED Devices (2,007 patents), which house electrical components (See also Table 2.1). These

[4] The company’s sample algorithm is included in Appendix A.
[5] I have adopted the process of data clearing that was done in publicly available patent datasets (e.g., NBER Patent Project by Professor Bronwyn Hall 2006).
[6] Derwent has four digit codes that represent the firm hierarchy.

subsystems and components are mutually exclusive and exhaustively represent the LED technology system, and yet each patent can be assigned to one or more components ("boxes"). Thus, the unit of analysis in this study is the knowledge embodied in different technology components of the patents. For example, one patent can represent two distinct types of component knowledge related to both substrates and optics.

Figure 2.1 LED technology system architecture



Note: LED technology system (Level 4); 4 LED technology subsystems (Level 3); 19 LED technology components (Level 2); 37 LED technology subcomponents (Level 1).

Table 2.1 LED technology system decomposition[7]

System	Level 3 subsystems	Level 2 components	Level 1 subcomponents
LED Technology System	LED Components	Lenses	Collimator lenses Fresnel lenses Parabolic lenses Other lenses
		Optics	Miscellaneous optical subcomponents
		Reflectors	Total internal reflection Other reflectors
		Thermal	Heatsinks Other thermal subcomponents
	LED Controls	Addressing	Miscellaneous addressing
		Analog	Miscellaneous analog
		Calibration	Miscellaneous calibration
		Color mixing	Color temperature change Other color mixing technologies
		Dimming	LED light dimming Other dimming subcomponents
		Network control	Authentication Intelligent systems networking Protocols Other network controls
		Power Management	Power distribution Power factor management Other power management subcomponents
		Pulse Width Modulation	Miscellaneous PWM subcomponents
	LED Devices	Dimmers	Analog dimmers PWM dimmers Other dimmers
		Drivers	Constant current drivers Constant voltage drivers Other drivers
	Chemistry & Materials	Bonding	Miscellaneous bonding subcomponents
		Epitaxy	Miscellaneous epitaxy subcomponents
		Packaging	Miscellaneous packaging subcomponents
		Phosphors	Automotive phosphor technology Remote phosphor technology Other phosphor technologies
		Substrates	Miscellaneous substrate subcomponents

[7] This table corresponds to the LED system architecture shown in Figure 2.1. Level 1 subcomponents are grouped to make Level 2 components. Level 2 components are grouped to make Level 3 subsystems. Level 3 subsystems are grouped to create the LED technology system.

Analysis: Design Structure Matrix

In order to capture the interdependence among multiple subsystems and components within the LED technology system, I adapted the principles and techniques of a method called the Design Structure Matrix (DSM). DSM is a network modeling tool for representing system elements and their interactions in a square matrix and thereby capturing a system's architecture with the help of visualization (Eppinger and Browning, 2012). The method has been used in various disciplines, from its original application in systems engineering (e.g., Thebeau, 2001) to its use in management science (e.g., MacCormack, Rusnak, and Baldwin, 2006; Sosa, Eppinger, and Rowles, 2004). DSMs are created in three steps. First, I choose the level of analysis and decide on the number of matrix elements that will represent each of the components within a system. The higher the level of analysis, the greater the aggregation of individual interactions. Second, the elements are listed in both rows and columns to create the square matrix. These elements are analogous to the nodes drawn in a network analysis. Third, the cells in the matrix are filled to represent the presence of dependence by a row on a column element (Baldwin, MacCormack, and Rusnak, 2014). Hence, across the row, I have all the components that a row component depends on. Down each column in the matrix on the other hand, I find all the components that depend on that column component. These interactions are analogous to the links in network analysis. Unlike other network analyses, one great advantage with DSM is that I can define the *direction* of dependence, a feature critical for the purpose of this study. I call this first-order matrix a Structure Matrix (Baldwin, MacCormack, and Rusnak, 2014).

For the purpose of this chapter, I report the results from the Structure Matrix in Level 2 with the LED technology system broken down into 19 technology components, i.e., 19 matrix elements (Table 2.1). I then entered the backward citations between LED technology patents into cells, representing the citation by a row component to a column component. For example, if epitaxy patents cited lens patents 10 times in year 1993, I have entered 10 in the row of epitaxy and column of lens, i.e., DSM (epitaxy, lens) in 1993 = 10. I also treated diagonals as non-empty entries, meaning a component can depend on itself. Twenty-six Structure Matrices are thus created for each year between 1981 and 2006, so that each matrix represents a *snapshot* of the architecture of LED technology system of the given year (Baldwin, MacCormack, and Rusnak, 2014; Sosa, Browning, and Mihm, 2007). Table 2.2 shows a sample Structure Matrix from 1990. The pre-commercialization period covers the period between 1981 and 2006.

From the Structure Matrix, I then constructed what is called the Visibility Matrix (Baldwin, MacCormack, and Rusnak, 2014; MacCormack, Rusnak, and Baldwin, 2006). The Visibility Matrix raises the Structure Matrix to a higher order, so as to represent the indirect as well as direct dependences between elements. Hence, the Visibility Matrix of the highest order in this study also captures the indirect dependence across 19 potential path lengths from one technology component to another. For the Visibility Matrices, I put binary values (1 or 0) for entries, indicating the presence of dependence rather than the strength of dependence (Table 2.3).

Table 2.2 Structure Matrix in 1990

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1	**lenses**	24	8	6	0	0	0	0	0	0	0	0	0	0	3	14	16	9	0	7
2	**optics**	14	8	6	0	0	0	0	0	0	0	0	0	0	0	10	8	6	10	10
3	**reflectors**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0
4	**thermal**	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	**addressing**	1	0	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0	0	0
6	**analog**	1	0	0	0	1	4	1	0	0	0	0	0	0	0	0	1	0	0	0
7	**calibration**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
8	**color mixing**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
9	**dimming**	2	0	0	0	0	1	0	0	1	0	0	1	0	0	2	0	0	0	0
10	**network control**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	**power mgmt**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	**pwm**	1	0	0	0	0	0	0	0	2	0	0	3	0	0	0	0	0	0	0
13	**dimmers**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	**drivers**	2	0	0	0	0	0	0	0	1	0	0	0	0	4	0	2	0	3	3
15	**bonding**	15	10	4	0	1	0	0	0	0	0	0	0	0	0	6	2	2	4	1
16	**epitaxy**	5	2	0	0	1	0	0	4	3	0	0	0	0	1	5	332	1	19	96
17	**packaging**	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2	0	3
18	**phosphors**	2	0	0	0	0	0	0	2	3	0	0	0	0	0	2	8	2	37	6
19	**substrates**	3	2	1	0	0	2	0	2	5	0	0	1	0	2	10	168	0	37	78

Note: This is LED technology system decomposition at Level 2, 19x19 DSM

Table 2.3 Visibility Matrix in 1990

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**lenses**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
2	**optics**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
3	**reflectors**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
4	**thermal**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
5	**addressing**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
6	**analog**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
7	**calibration**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
8	**color mixing**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
9	**dimming**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
10	**network control**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	**power mgmt**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	**pwm**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
13	**dimmers**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	**drivers**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
15	**bonding**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
16	**epitaxy**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
17	**packaging**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
18	**phosphors**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
19	**substrates**	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1

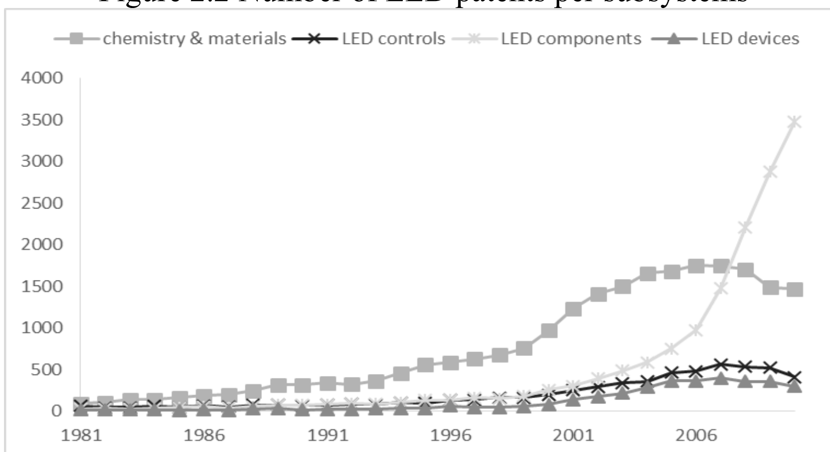
Note: This is LED technology system decomposition at Level 2, 19x19 DSM

Propositions

Emerging Technology in Multiple Life Cycles

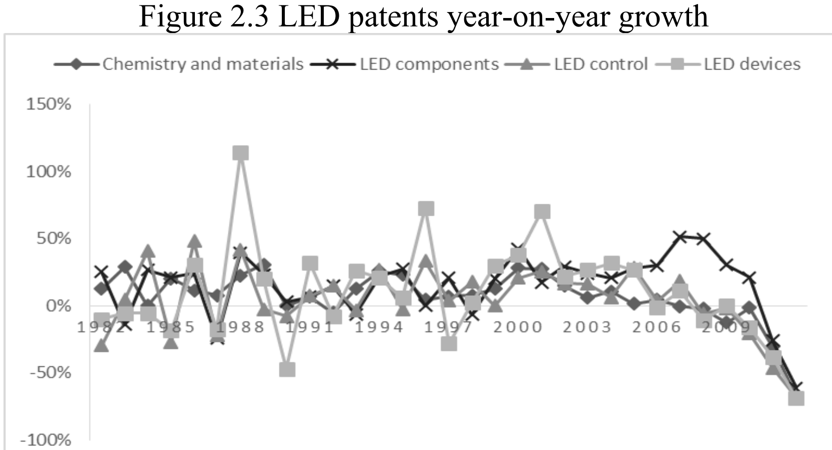
The literature of technological change notes that such change starts with innovation in the core technology, which is followed by innovation in complementary technologies (Rosenberg, 1969). This study shows that LED development has unfolded in multiple layers of technology components, which together make up a new lighting system. The LED industry's early focus was to research and develop the core technology, which is the semiconductor light source. As shown in Figure 2.2, the LED industry's efforts were primarily in chemistry and materials (including phosphors, epitaxy, and substrates). In the first decade or so of my sample period, these two areas make up twice as many patents as those of the other three subsystems (LED components, controls and devices) combined. Such efforts precede the product commercialization by an order of decades; they also long precede the invention that showed the first potential for LEDs' application in general illumination (the "technological breakthrough"), the Noble Prize-winning invention of the blue LED in 1993. It is notable that the development in complementary technologies parallels that in the core technology, albeit at disparate growth rates (Figure 2.3). The advancement in optics, for example, is in large part due to the industry's need to improve light distributions from LEDs, which are directional point sources. When the growth of chemistry and materials patents started to hit a plateau, complementary technologies "enabled" by the LED core technology showed an exponential growth starting in the few years preceding 2007, the year the LED lamps were first commercialized.

Figure 2.2 Number of LED patents per subsystems



Note: This graph pictures on the y-axis the number of patents filed in each of four LED subsystems over 1981-2010. When each patent includes technological knowledge in more than one subsystem, it is counted multiple times.

Figure 2.3 LED patents year-on-year growth



Among subsystems of complementary technologies, there is also variance in their growth rate. For instance, whereas optical advancement starts at the beginning of the sample period, technologies surrounding electrical components such as drivers arrive much later.

I thus propose that technology life cycles of an emerging industry unfold in a nested hierarchy of multiple subsystems, which exhibit respective patterns of development.

> *Proposition 1: Technology evolution of an emerging industry is formed by multiple technology subsystems and components, which are nested in hierarchy.*

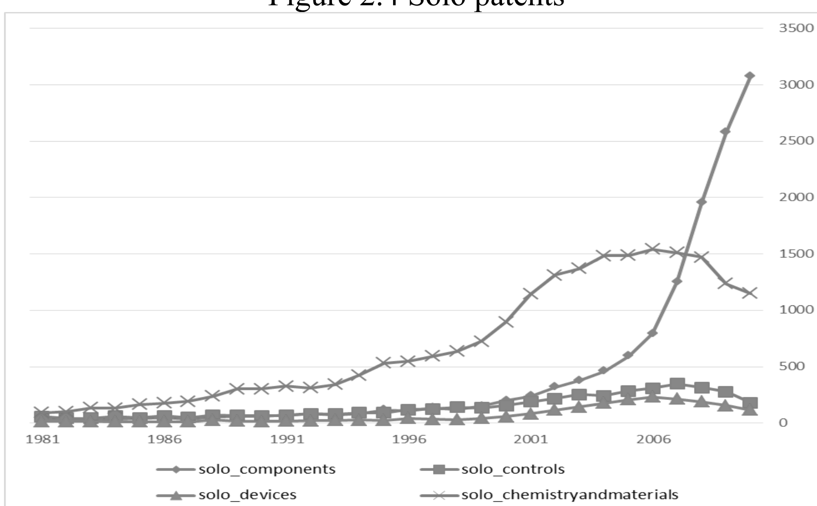
> *Proposition 2: Technology evolution of an emerging industry begins in the core technology subsystem, followed by that in complementary technology subsystems.*

From Modular to Architectural Knowledge

After identifying the temporal development of four LED technology subsystems in the previous section, I next examine whether the nature of knowledge itself evolves and in what manner. Studies indicate that knowledge can be either modular or architectural in nature (Henderson and Clark, 1990). Product innovation necessitates both modular knowledge, the knowledge about a particular technical component, and architecture knowledge, the knowledge of how components are linked together to create a whole (Baldwin and Clark, 2000; Henderson and Clark, 1990). Following this theoretical distinction, I analyzed the LED patents in 4 groups: 1) solo patents that embody knowledge about a single component and thus a single subsystem, e.g., a patent about substrates; 2) duo patents that embody knowledge spanning two subsystems, e.g., a patent containing knowledge about substrates (chemistry and materials subsystem) and lenses (LED component subsystem); 3) trio patents that embody knowledge spanning three subsystems; and 4) quartet patents spanning four subsystems. This grouping increases in the degree of integrativeness of knowledge in a patent: solo patents represent modular knowledge and other three groups represent architectural knowledge or system-level knowledge in the case of quartet patents.

Figure 2.4 depicts that the evolution of solo patents mimics a pattern of the overall trajectory described in above section. This is quite expected since the solo patents take up a lion's share of the total number of patents. For example, the knowledge in the core technology subsystem – chemistry and materials – ceases to grow after year 2004 or so.

Figure 2.4 Solo patents



However, the evolution of other three groups of patents, together called the group of architectural knowledge, shows a stark difference as shown in Figure 2.5-7.

Figure 2.5 Duo patents

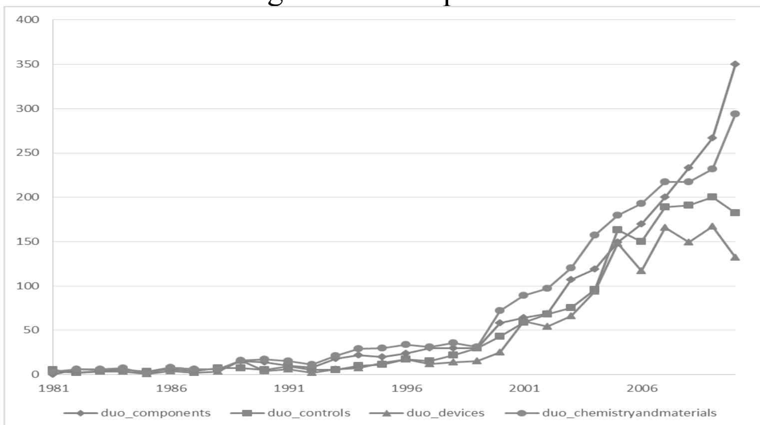


Figure 2.6 Trio patents

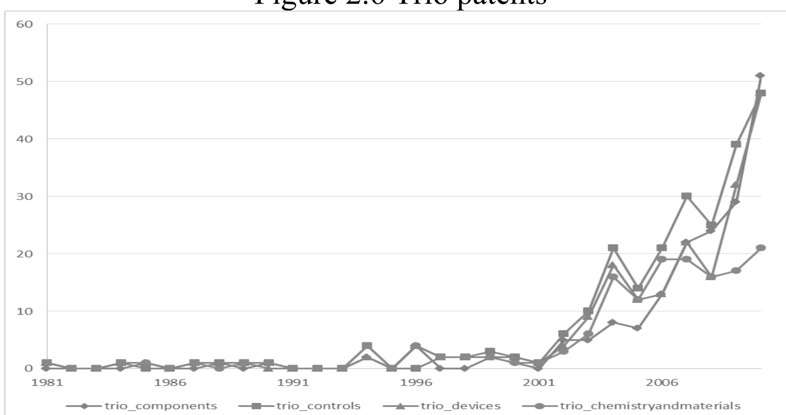
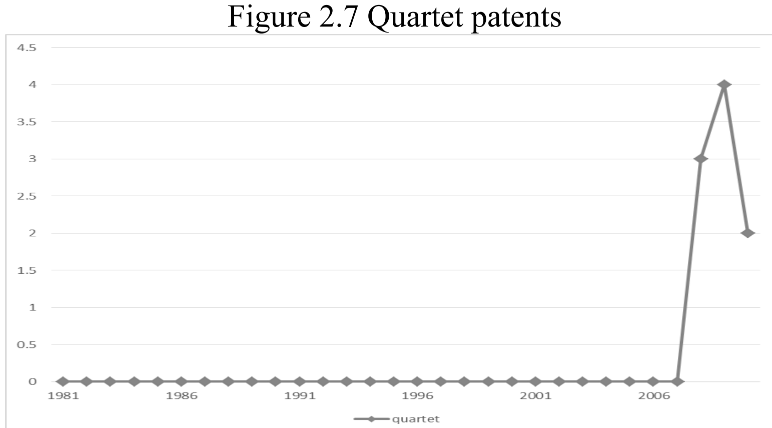


Figure 2.7 Quartet patents



Duo, trio and quarter patents involving any LED subsystem have grown especially after year 2001 or so. They interestingly appeared in a sequential pattern where quartet patents came out after trio patents (in 2002: before 2002, average number of patents was 1) that appeared after duo patents, which had been present since the initial year of our study and showed 94% growth rate between 1999 and 2000. In sum, architectural knowledge emerges after modular or component-specific knowledge during the pre-commercialization life cycle. While all six combinatorial[8] of duo patents exhibited the steady growth rate during the whole study period, particularly two types of duo patents, one spanning LED components and chemistry and materials and the other spanning LED controls and devices, are worthwhile to examine more closely. They show exponential growth rate after 1999 and 2000 while other types of duo patents begin to slow down after 2000. The duo patents that connect component and chemistry and materials knowledge recorded a 10-year average year-on-year growth rate of 31.4% and those connect LED controls and devices knowledge, 29.2%. This empirical evidence shows the heterogeneity in architectural knowledge in the industry, suggesting that the evolution of architectural linkages in a technology system entail essential bearings on theories of knowledge evolution.

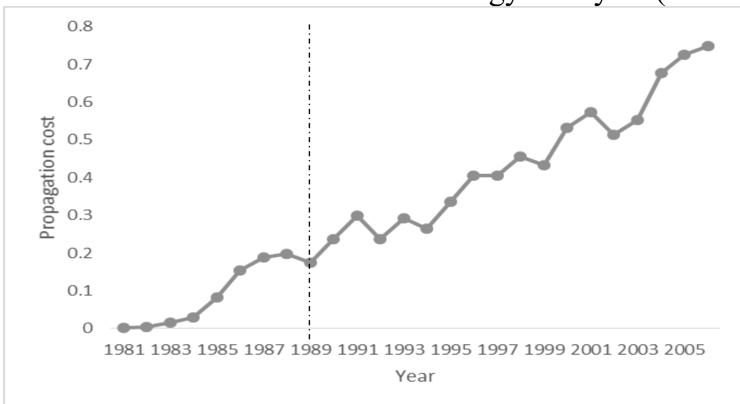
> *Proposition 3: Industry knowledge evolves from being modular to architectural in nature.*

[8] 4C2

Evolution of Technology Architecture at the System Level

Above, I illustrate that multiple technology subsystems and components take their own evolutionary paths. Notwithstanding their respective evolution, a technology system displays an important architectural property over time at the system level: the degree of modularity. Modular systems are exemplified by the high level of integration within the same module and the near independence across the different modules (Schilling, 2000; Simon, 1962; Yayavaram and Ahuja, 2008). Interdependent systems, on the other hand, are exemplified by the high level of integration across the different modules. Baldwin and Clark (2000), for instance, document that an industry evolves towards increasing modularity, for example through the division of labor. I argue that knowledge can also be modularized (Brusoni and Prencipe, 2001) and thus study the interdependence level of an emerging LED system over time. In order to understand the architectural evolution at the system level, I used a tractable measure called *propagation cost* (MacCormack, Rusnak, & Baldwin, 2006; Baldwin et al., 2014), which captures the interdependence level of the LED technology system over time. By definition, it is the percentage of components that also change when a change has been made to a randomly selected component in a system. Therefore, the higher the propagation cost, the more integrated the system, or the less modular the system. My method for calculating propagation cost is detailed in Appendix B. Plotting this over the sample period, I find that an emerging technology's architecture becomes more integrated over time during the pre-commercialization period (Figure 2.8).

Figure 2.8 Pre-commercialization technology life cycle (1981-2006)



Note: This figure plots on y-axis the propagation cost (PC) at the LED system level over time. It is calculated as follows:

$$\text{propagation cost}_t = \left(\frac{\sum \text{VFI}_{jt}}{19}\right)$$

where Visibility Fan In (VFI) of component j in time t indicates the number of components that cite component j in year t. At the system level, the propagation cost of year t will represent the average VFIs of 19 components.

This is an interesting finding compared to what we know of post-commercialization technology evolution, which moves towards increasing, not decreasing, modularity over time (Baldwin and Clark, 2000). In the post-commercialization period of the emergence of a dominant design, an industry becomes modularized, given the standardized technical interface of a new product (e.g., Suarez and Utterback, 1995).

> *Proposition 4: An emerging technology system becomes more integrated over time during the pre-commercialization period.*

I observe not only the general pattern towards an architectural integration, but also what seems like a tipping point, after which a shift occurs and the second pattern takes over .

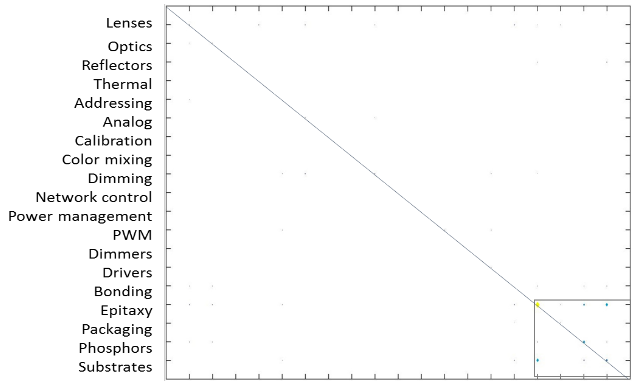
In order to understand what is driving such shift at the system level, I investiage how the interdependence level changes at the component level, an issue I turn to next.

From the Era of Modularity to the Era of Integration

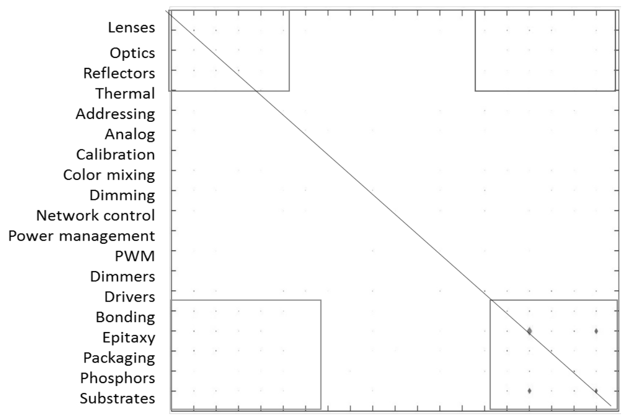
Not only do technology life cycles unfold in multiplicity, they also exhibit varying degrees of architectural properties in underlying component technologies. The technology architecture of a new industry evolves at the component level as follows: First, the interactions reside within the same subsystem. The core technologies ("chemistry and materials" knowledge) only interact with each other first (measured by patent citations); and complementary technologies form their own clusters of knowledge in the early years (Figure 2.9: Panel A). A few years later, chemistry and materials subsystems start to draw knowledge from complementary technologies, represented by the off-diagonal matrix entries. Then, the "LED components" subsystem begins to draw knowledge from the core technology. Over time, other subsystems appear, and the system becomes more integrated (Figure 2.9: Panel B).

Figure 2.9 Modular and interdependent system

Panel A. DSM in 1986, Modular system



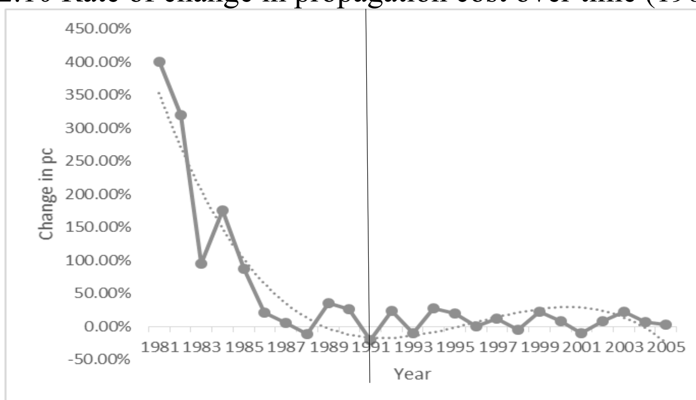
Panel B. DSM in 1996, Interdependent system



Note: Two panels provide the DSM visualizations indicating technology component interactions within the LED technology system. Panel A exhibits an exemplary modular system where interactions are modularized within the subsystem. Panel B exhibits an exemplary interdependent system where interactions span across the subsystems.

After 1989, the interactions span the entire architecture; and there is no change in the year-on-year growth rate of propagation cost at the system level. As in Figure 2.10, after this point, there is no change in the rate of increase in the propagation cost of the LED technology system over time.

Figure 2.10 Rate of change in propagation cost over time (1981-2006)



Note: This figure plots the rate of change in propagation cost at the LED technology system level over time. For example, 150% indicates there was a 150% increase in the propagation cost from 1983 to 1984.

I have termed the first phase, when the interdependence across components begins to operate across subsystems, “the era of modularity,” and the second phase, the years after such interdependence has spanned the entire architecture of the system, “the era of integration”. (Figure 2.11)

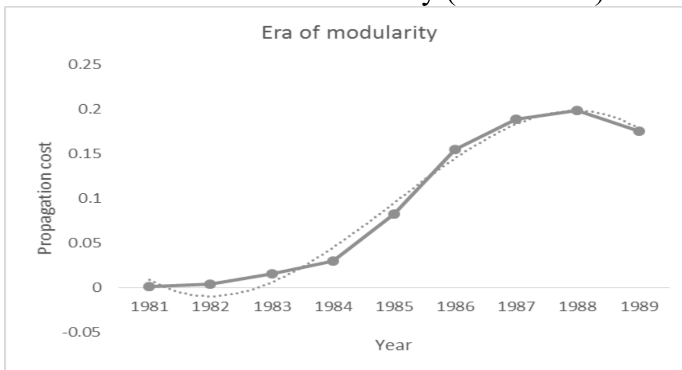
Proposition 5: Within-subsystem interdependence comes before across-subsystem interdependence.

Proposition 6: The number of subsystems interacting increases during the era of modularity.

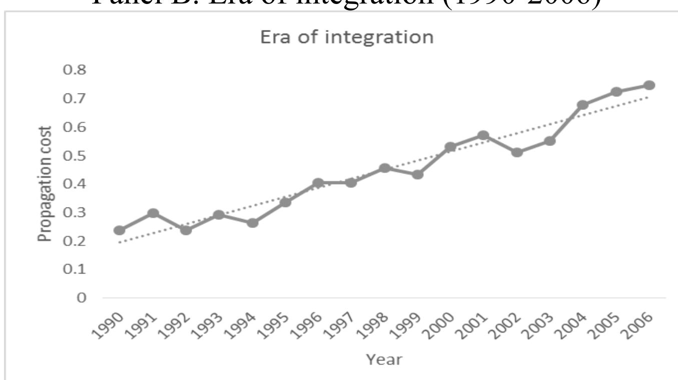
Proposition 7: The era of integration follows after the interactions across technology subsystems all become bi-directional.

Figure 2.11 Era of Modularity to Era of Integration

Panel A. Era of modularity (1981-1989)



Panel B. Era of integration (1990-2006)



Note: Panel A magnifies the era of modularity. The propagation cost at the system level seems to follow what looks like an S-curve over time: first it grows very slowly for the initial four years and then increases exponentially before it stabilizes. Panel B magnifies the era of integration. The propagation cost at the system level here shows no change in the rate of change over time.

Discussion and Conclusion

Research from multiple disciplines suggests several themes that generate insights into the internal mechanisms of technological change (Rosenberg, 1982). Yet more than three decades after this call to action, the black box of the pre-commercialization phase has remained sealed, and its secrets, of how scientific knowledge underlying industry emergence evolves, unrevealed. I argue and empirically demonstrate that patterned changes occur in the evolution of a new technology's architecture as it moves towards commercialization. I study how a new technology evolves in the nested hierarchy of a system by extending the horizon back to the pre-commercialization period.

I first show that the technical development of a new product does not unfold unilaterally as a single-layered invention. Instead, each technology subsystem exhibits its distinct life cycle in a disaggregated manner. Technology evolution begins in the core technology invention well before the first instance of product commercialization; this core technology leads to the consequent development of complementary technologies. In LED, the epochal moment came in 1993 when high-brightness blue LEDs were invented, making the white LED light possible. This instance would have been generally marked as "technological discontinuity" in the received literature. However, I show that such a breakthrough invention has taken a smooth trail of scientific advancement rather than emerging at a punctuated moment of discovery, if we pay attention to the entire pre-commercialization phase. Furthermore, the evidence suggests that by the time products are commercialized, complementary technologies have also made the remarkable advancement, enabling the effective LED lighting system to finally emerge.

Furthermore, in conjunction with *Proposition 4,* I provide the first empirical evidence of how the architecture of a pre-commercialization technology system changes over time. The separation of the LED technology system into subsystems and components enables an investigation into the architectural linkages a technology system embodies. Patent backward citations are conceptualized as interactions, thus indicating the knowledge interdependence among technology components in a given year. As the interdependence at the component level increases, the greater the integration at the system level, as explained above. Moreover, in conjunction with *Proposition 7*, there seems to be a tipping point, after which a shift occurs and the second phase takes over. My evidence from the DSM analysis shows that the second phase, which I term "the era of integration," arrives only after the interactions among all the technology components have become *bi*-directional. From then on, I show that there is no change in the percentage growth rate of propagation cost from the previous year, which is a feature of a fully integrated system. The time when any given technology component becomes dependent directly or indirectly on all other components in a system occurs even before the product (in this case, a solid-state lighting product) is first commercialized. Such architectural integration is in stark contrast to the post-commercialization technology life cycle, which the literature shows moving towards modularization (Baldwin & Clark, 2000; Anderson and Tushman, 1990). This may imply that interactions across the entire technology system make the basic understanding of an emerging technology interface complete and allow for a new product market to take off.

This study makes two main contributions. To my knowledge, this is the first empirical study to shed light on the pre-commercialization technology life cycle. Recent work uncovers an active period of technology exploration before the inception of an industry (Moeen and Agarwal, 2016). I contribute to growing studies in this field by showing that there is indeed "life before a life cycle" and that the pre-commercialization period exhibits the pattern of a life cycle distinct from that of the post-commercialization period. In solid-state lighting, the pre-commercialization period is characterized by immense inventive efforts (over 30,000 patents in the LED) in the core as well as complementary technologies that can lead to new product innovation. Therefore, what seems like a "discontinuity" at an aggregate level can instead be a continuous, accumulative process of exploration. As such, product innovation in nascent industries must be endogenized so as to include the inventive efforts in diverse technology fields during the pre-commercialization period.

Second, I contribute to bridging modularity and industry evolution studies by uncovering the underlying mechanisms driving the technology system-level integration. I particularly focus on the evolution of architectural properties of the LED technology system, emphasizing the changes in the linkages across diverse components. By introducing the concept of propagation cost from the modularity literature, I illustrate how to track the interdependence among different knowledge components that make up a solid-state lighting over time and show the pattern of architectural evolution. Using this approach, I find that the pre-commercialization period is divided into two phases—the era of modularity and the era of integration—which are differentiated in terms of the architectural properties technology components exhibit.

CHAPTER 3

INCUMBENTS' PRE-COMMERCIALIZATION SEARCH: A MIRRORING HYPOTHESIS

Introduction

Recent studies increasingly indicate that large, established firms, not just new firms, invest in emerging technology fields (e.g., Eggers, 2014, Jiang, Tan, and Thursby, 2011; Wu, Wan, and Levinthal, 2014). This line of research illustrates that despite the prevailing notion that compared to new and nimble firms incumbent firms may be at a disadvantage in leveraging the nascent technological knowledge into market opportunities (Henderson and Clark, 1990; Tripsas and Gavetti, 2000), they are not completely oblivious about emerging technologies that could directly affect their existing capabilities and complementary assets (Jiang, Tan, and Thursby, 2011; Tripsas, 1997; Wu, Wan, and Levinthal, 2014). Research shows that established organizations can, in fact, invest in a nascent technology, even before the potential for its new market application becomes evident (Cattani, 2005). In sum, limited yet growing empirical evidence makes clear the benefit of mastering new technologies before their new market application; and yet the question of how firms conduct such exploratory search is still underexplored.

The bulk of industry evolution research has focused on finding systematic differences in performance (Christensen, 1997; Khessina and Carroll, 2008; Klepper and Simons, 2000), mortality rate (Agarwal, Sarkar, and Echambadi, 2002; Carroll *et al.*, 1996; Chen, Williams, and Agarwal, 2012), and technology choices (Bayus and Agarwal, 2007; Kapoor and Furr, 2014) across *de alio* and *de novo* entrants when new industries emerge. In contrast, the heterogeneity *within* a group of established firms has been largely overlooked compared to the studies of *de alio* versus *de novo* dynamics. Sosa (2013) partially attributes this oversight to the unclear distinction between the "new industry" and "creative destruction" research. For instance, previous studies have focused on the strategies and performance of *de alio* entrants because at the inception of a nascent industry (e.g., the automobile industry in Carroll *et al*. (1996), the TV industry in Klepper and Simons (2000)), everyone is a new entrant – *de alio* or *de novo* entrant. Yet, in the "creative destruction" research that targets the phenomenon of industry evolution going through phases of technological transitions (Adner and Kapoor, 2015; Henderson and Clark, 1990; Tushman and Anderson, 1990), we observe incumbent organizations which, if successful, live through the next generation of products (Sosa, 2013). This distinction in the industry evolution literature is not clear, and studies follow the tradition of implicitly assuming that there is no incumbent firm in a "new" industry and leaving the adaptive behaviors of incumbents out of the discussion. Even after allowing for such technical misconceptions, the lack of scholarly attention to the heterogeneous behaviors within a group of established organizations at the face of a technological change is quite surprising, given that a new industry often embodies multiple converging technology fields. Studying the era preceding commercialization is therefore worthwhile, since it forces me to uncover the inventive activities of firms that all have pre-organizational history before the inception of a new industry (Sosa, 2013).

Scrutinizing pre-commercialization evolution in this study is therefore a direct investigation into how firms would (or would not) develop pre-(market) entry experiences and capabilities in the anticipation of an industry emergence. In this chapter, I compare the search strategies deployed by two important groups of established organizations during the pre-commercialization life cycle theorized in chapter 2. The first group includes those firms experiencing technological obsolescence in an existing market segment. The second group includes a group of firms that reside outside the boundary of the focal industry going through a transition, but who have a directly relevant technological capability that can disrupt an existing industry (Christensen and Rosenbloom, 1995; Klepper, Baum, and McGahan, 2004; Klepper and Simons, 2000). The latter group is therefore one type of potential diversifying entrant, as discussed in the literature (Carroll *et al.*, 1996; Helfat and Lieberman, 2002). The first group is therefore coined *market incumbents* and the second *technology incumbents*. Market incumbents in the context of this study are traditional lighting firms, such as Cooper Lighting, which has downstream incumbency in lighting applications. This group of firms faces innovation challenges propelled by the advent of the high brightness light emitting diodes (LEDs) that can replace incumbent technologies such as incandescent lighting. Technology incumbents, on the other hand, are semiconductor firms such as Samsung Electronics, whose upstream semiconductor-related knowledge and resources are deployable in a lighting market. Technically, they can potentially make a market entry into a new solid-state lighting industry. Other exemplary cases in the literature would be nanotechnology firms moving into the semiconductor industry (Jiang, Tan, and Thursby, 2011) and recombinant DNA firms moving into the anticancer drug market (Sosa, 2013). Both types of incumbents can develop distinctive capabilities during the pre-commercialization period and face different innovation challenges at times of an industry emergence. More specifically, the two different types of incumbent organizations engage in different search strategies during the pre-commercialization phase, a question I preview below.

I argue that the two types of incumbents differ in the way they design a technology architecture; specifically, they create different dependency structures, moving either towards integrating or towards modularizing individual technology components across the pre-commercialization technology life cycle. In hypothesizing firms' search strategies at the backdrop of the pre-commercialization life cycle theorized in chapter 2, I incorporate from modularity literature the insight that firms tend to align the architecture of a problem they are trying to solve with their organizational designs. Such optimizing behavior is referred to as "mirroring" in the modularity literature (Colfer and Baldwin, 2010). Consequently, I first hypothesize that both types of incumbents will "mirror" the system-level integration such that they will integrate the knowledge underlying technology components to a greater degree during the era of integration than they will during the era of modularization.

Subsequently, however, I argue that the extent to which they "mirror" will vary depending on which type of incumbency from which they operate. These arguments are based on the premise that market and technology incumbents would face different types of innovation challenges and degrees of uncertainty over the life cycle of a pre-commercialization phase. Studies show that when making boundary choices, firms tend to integrate more rather than less at times of uncertainty (Grant, 1996). For example, system integrators would invest in the knowledge of component technologies whose pace of development is unevenly rapid (Brusoni, Prencipe, and Pavitt, 2001). I argue that firms will integrate knowledge about different components of an emerging technology system to a greater extent, i.e., *technology architecture* is more integrated, when they face greater levels of uncertainty.

In order to test my firm-level hypotheses related to the technological search of market and technology incumbents, I rely on a sample of publicly traded US and non-US firms operating in lighting and semiconductor industries during the pre-commercialization period of a US solid-state lighting market. Out of a total of 30,840 US-granted patents between 1981 and 2006 from chapter 2, 2,286 patents match to either lighting or semiconductor firms during the pre-commercialization period of a solid-state lighting market.

I first develop arguments leading towards a system-level proposition: the pre-commercialization technology system starts off with a modular architecture and assumes an integrated architecture of subsystems and components over time. I deepen the understanding of the mechanisms causing such an architectural shift by showing how they are related to the types of uncertainties each incumbent group will face for product innovation. I particularly focus on explaining the different innovation landscapes born before and after the breakthrough invention, the advent of high-brightness blue LEDs. I show that such a shift influences the search behaviors of lighting and semiconductor firms differently, and find support for the hypothesis that technology incumbents, namely semiconductor firms, move towards a more integrative search approach than do lighting firms at the moment of "technological discontinuity." This result is robust after controlling for technology component- and year-fixed effects.

I make two important contributions to the studies of industry evolution and organizational search. First, I provide an empirical account of the pre-commercialization inventive activities of established organizations facing technological changes. A theme in the literature has been that incumbent organizations have a difficult time riding the waves of creative destruction (Christensen, 1997; Henderson, 1993). As they may be subject to such a disadvantage, I argue and empirically demonstrate that established organizations do undertake exploratory search during the pre-commercialization period. The primary focus of my study is firms' evolutionary journeys. I argue that firms not only search for new technological opportunities in the pre-commercialization phase, but also evolve in terms of their search strategies across the pre-commercialization life cycle. My study thus addresses a selection issue rampant in the industry evolution literature: firms' endogenous entry decisions, arising from the habit of tracking industry evolution from the inception of a product market. By providing heterogeneity in the way firms develop pre-entry knowledge, the findings from this study can offer a systematic explanation of the effect of pre-entry experiences on post-market performance.

Second, I study how incumbents with different capabilities maneuver across the changing technology landscape in the infant years of a new technology. I show that market incumbents behave differently from technology incumbents that are not yet operating in a focal product market but that do possess the knowledge of an emerging technology. The latter type of organizations is given little attention in the literature, as often the threat is assumed to have originated exogenously. I show that these two groups of incumbents do invest in emerging technology fields, but that they do so differently. This study offers the first direct investigation into both market and technology incumbents' development of pre-(market) entry experiences and looks closely at the early design choices that established organizations make in the anticipation of a new industry. The outline of this chapter is as follows. I first lay out a proposition related to the pre-commercialization technology life cycle. Then, I move to formulating predictions on organizational search along such a life cycle. I introduce firm-level data, an empirical model and analysis, and discuss important implications from the findings of this chapter.

System-Level Proposition: Evolution of Technology Architecture

A technology life cycle undergoes stages of development across a watershed event such as the emergence of dominant designs. Scholars find that the technological landscapes and competitive conditions shift after such landmark event (Anderson and Tushman, 1990; Agarwal, Sarkar, and Echambadi, 2002). An equivalently impactful watershed event during the pre-commercialization phase is the introduction of a technological invention in the scientific community, such as the Nobel Prize-winning invention of the blue LED, or that of genetic engineering technology (Kapoor and Klueter, 2015), which can potentially create the winds of destruction in a distant market. In the literature, such an advent is commonly referred to as a "technological breakthrough" or "technological discontinuity" (Tushman and Anderson, 1986). As I discussed in chapter 2, previous studies treat such invention as an exogenous shock to an existing industry and track industry evolution from the new product's life cycle.

In this study, I focus on how the pre-commercialization *life cycle* unfolds before and after the "breakthrough" watershed event. Instead of assuming its exogeneity, I try to highlight the innovation landscapes before and after a breakthrough invention as a new technology journeys through the entire pre-commercialization phase. In so doing, I highlight two mechanisms by which an emerging technology system assumes an integrated architecture. First, I rely on the notion of the performance bottleneck present in complementary technologies attempting to catch up with the improvement in the core technology subsystem (Hughes, 1983; Rosenberg, 1979). Second, I highlight the decreased uncertainty around the potential of a focal invention with respect to its application in a new market setting. For example, the invention of blue LEDs has made evident their application in general illumination beyond the consumption in signage or other consumer electronics markets (e.g., calculators). I argue that a pre-commercialization technology architecture will be more integrated as it faces the breakthrough invention with the above two mechanisms in place. From another perspective, these mechanisms underlie the propositions from chapter 2 about the increased interdependence across different components during the era of integration. In this chapter, I try to elaborate on why components move towards interdependence.

The phase before a breakthrough invention is characterized by inventive efforts within independent subsystems of the core and complementary technologies. During this early phase, absent explicit demand-side feedback, the nature of inventive activity is thus akin to what Dosi (1982) termed the "mechanisms and procedures of science," wherein the focus is on unraveling problems that are localized to each cluster of technology, but which over time will coalesce and recombine into what would be known decades later as “radical innovation.” The majority of efforts are geared towards improving the performance of the core technology (in solid-state lighting, the light output of the blue LED chip), before spreading to efforts to achieve further advancement in complementary technologies such as optics. The interactions between core and complementary technology subsystems are minimal, and innovation clusters are highly localized. This modular process of knowledge exploration will continue until a “breakthrough” arrives.

In contrast, after the “breakthrough,” the need for architectural and systematic knowledge (Grant, 1996; Henderson and Clark, 1990), rather than modular knowledge, is heightened for two reasons. First, the innovation efforts now focus on overcoming the performance bottleneck faced by complementary technologies. For example, the development of transistor radios had to await major improvements in purified metal (Rosenberg, 1979). In solid-state lighting, the light output from the LEDs could not rise to the level of that of conventional lighting sources until a Japanese scientist, Shuji Nakamura, invented the first LEDs on Gallium Nitride (GaN) to enable the white light revolution (Nobelprize.org, 2014). Achieving such performance equivalence to traditional lighting sources with LED technology (Figure 1.1) consequently forced complementary technology domains such as optics and thermal controls to improve in order to incorporate knowledge from the core invention. The interdependence among different technology components, e.g., substrate development and thermal controls, becomes highly significant as a technology system moves towards its first commercialization in a new market setting such as general illumination.

Second, the breakthrough invention takes away the uncertainty around what impact it might have to a new market setting. For example, in solid-state lighting, Nakamura's blue LED invention has made evident that the LED technology will disrupt the traditional lighting market. As the uncertainty around LEDs' market potential was resolved, both the semiconductor and lighting industries started to work on improving other complementary technologies that would enable "LED light" beyond enhancing the light output, e.g. dimming technology. Given that the invention of the LED invention was radical in nature to the incumbent lighting industry, the high level of knowledge integration across LED key components and other complementary lighting technologies was a hallmark of successful innovation. After the watershed invention, the locus of innovation now moves on to connecting the dots in an emerging technology system and achieving the systematic innovation from a given breakthrough invention rather than remaining as the masters of the component knowledge (Rosenberg, 1979). The above arguments suggest that an emerging technology system will move towards an integrated architecture as it journeys across the advent of a breakthrough invention.

> *Proposition: Technological system during the pre-commercialization phase will evolve from a modular to an integrated architecture after the technological breakthrough.*

Technology Mirroring

I next explore how incumbent firms search over the course of the pre-commercialization technology life cycle discussed above. The pre-commercialization phase can be a pathway for firms to understand a basic architectural design of an emerging technology system. Taking this viewpoint, established firms look less like victims of creative destruction. Rather, scholars show evidence that the established organizations as well as *de novo* entrants invest heavily in emerging technological fields before the onset of a new (product) market (Eggers, 2014; Kapoor and Klueter, 2015; Jiang, Tan, and Thursby, 2011; Moeen and Agarwal, 2016). However, the question of how these incumbent organizations search for new knowledge during the pre-commercialization life cycle is still unanswered. Will established organizations engage in more integrative search towards commercialization as the pre-commercialization period goes through an architectural integration? As many studies emphasize the impact of organizational search on innovation performance (Katila and Ahuja, 2002), our understanding of incumbent firms' pre-commercialization search strategies can shed light on how they survive the winds of creative destruction.

In the modularity literature, the "mirroring hypothesis" is defined as the architectural correspondence between an organizational design and the architecture of a product under development (Colfer and Baldwin, 2010; Henderson and Clark, 1990; MacCormack, Baldwin, and Rusnak, 2012; Sosa, Eppinger, and Rowles, 2004). For example, if two components of a product are highly interdependent, one would expect a high degree of interaction between the two teams developing the components in question. Since the architectural knowledge gets embedded in routines, structure, and cognitions, the organizational architecture begins to reflect the product architecture. In this respect, Henderson and Clark (1990) argue that architectural inertia becomes a key reason why incumbents fail to unlearn and adapt when the dependency structure among components changes due to an external shock. Hence, the mirroring hypothesis echoes the need to design an organizational search so that it is best aligned to solve the problem at hand (Ethiraj and Levinthal, 2004; Nickerson and Zenger, 2004).

As a new technology system emerges, the nature of the problem facing an organization changes, from mastering one technology component to understanding the emerging linkages between the different technology components that make up a new technology system. Following the mirroring hypothesis, I argue that the firm-level search strategies also need to evolve in correspondence with the evolution of a nascent technology system. I here refer to firms' optimizing behaviors as "mirroring" and argue that incumbent firms will align their search to the evolving architecture of a technology. That is, firms will focus on deepening knowledge within individual technology components before the breakthrough invention. However, after the introduction of a breakthrough invention, they will engage in more integrative search by trying to understand the linkages between different components in an entire architecture. Therefore:

Hypothesis 1: After the breakthrough invention, incumbent firms will engage in more integrative search.

The Moderating Role of Incumbent Experiences

Scholars have long contended that firms make path-dependent choices based on their historical capabilities and resources (Helfat and Lieberman, 2002; Helfat and Raubitschek, 2000; Qian, Agarwal, and Hoetker, 2012; Wu, Wan, and Levinthal, 2014). Although we have a relatively good understanding of the idiosyncratic choices firms make *post*-commercialization due to their heterogeneous pre-entry experiences, we have little evidence of *how* such heterogeneous experiences are developed by firms before entering a new market (Kapoor and Klueter, 2015). Understanding such pre-commercialization heterogeneity is important because it has significant post-commercialization bearings. For example, scholars uncover that pre-commercialization technology choices have direct consequences on subsequent product performance (Eggers, 2012b; 2014). In this section, I provide a direct investigation into how market and technology incumbents search for knowledge about a new technology during the pre-commercialization phase. I argue that the extent to "mirror" the evolving technology architecture, or the degree to engage in integrative search, will differ between market and technology incumbents.

Firms make idiosyncratic knowledge boundary choices irrespective of product boundaries (Brusoni, Prencipe, and Pavitt, 2001; Kogut and Zander, 1992; Grant, 1996). In the pre-commercialization period, firms search for new knowledge even though they have not yet made a commercialization choice. A common theme in the literature suggests that heightened uncertainty forces firms to solve the specific innovation problems in-house rather than to "buy" the external resource or knowledge. In other words, they tend to integrate rather than modularize. For example, system integrators would develop knowledge about the components they do not manufacture in times of technological changes (Brusoni, Prencipe, and Pavitt, 2001; Kapoor and Adner, 2012). I argue that market and technology incumbents will integrate the knowledge within an emerging technology system to a greater extent when they perceive the higher uncertainty at hand.

Types of uncertainties in the pre-commercialization phase are two-fold. As I explained above, one type of uncertainty is related to the deployment of a focal technology in a new market application (Cattani, 2005; Rosenberg, 1969). The innovation challenge surround this core invention subsides after the watershed event during the pre-commercialization phase. Another type, which remains to be understood, is the interface between the core and complementary technologies, which is necessary not only for completing the lighting system but also for facilitating market adoption. For solid-state lighting, after Nakamura's blue LED invention in 1993, the industry embarked on collective efforts to raise the consumer acceptance of LED light bulbs by working on color improvement and dimming solutions.

Incumbents who have existing downstream capabilities related to the market application of a new technology will face less uncertainty in terms of understanding the interface between a core technology and complementary technologies than those trying to enter into a new market space with only an upstream technological knowledge. In the context of this study, semiconductor firms significantly lack the understanding of a lighting application, and more importantly they face greater challenges in understanding the intricate interface across the upstream and downstream technologies. For instance, in solid-state lighting, semiconductor firms first needed to work on improving the performance of LED chips before the Nakamura's breakthrough invention. Such inventive efforts form their core knowledge. Yet after the breakthrough invention, when it became evident that LEDs could be applied to general illumination, those technology incumbents had to produce LEDs that could better function with the existing dimming technology. In other words, as technical uncertainty is largely resolved in an industry, their challenge is to understand the undiscovered interdependence between LEDs and complementary technologies to enable "solid-state lighting". Lighting firms, although they do not necessarily manufacture LED chips in-house, possess better understanding of a lighting application and which lighting qualities (e.g., warmth of light) are important for consumers. In sum, technology incumbents face greater uncertainty after the breakthrough invention than would market incumbents. Therefore:

> *Hypothesis 2: The extent to engage in more integrative search ("mirror") after the breakthrough invention is less for market incumbents than for technology incumbents.*

Data

From the total set of 30,840 patents, I focused on a select sample of patents filed by firms in line with my hypotheses. My sample of firms engaging in pre-commercialization search in the LED technology space includes publicly traded US and non-US semiconductor (SIC 3674) and lighting (SIC 3640) manufacturers who have at least one LED patent that cites at least other one LED patent during 1981-2006. Using fuzzy matching, I merged the original patent data set with data from Compustat North America and Compustat Global to construct firm-level data. If a Compustat firm has multiple subsidiaries independently filing LED patents (for example, Philips Lighting and Lumileds), I treated the relative patents as falling under the umbrella of a parent firm and thus aggregated the patents within a corporate hierarchy. This way, I did not lose the sample of patents that are filed by private subsidiaries of parent firms that appear in the Compustat database. As a result, 2,286 patents were filed in my sample of 15 lighting firms and 82 semiconductor firms between 1981 and 2006.

Empirical Model and Measures

I test 1) the mirroring hypothesis that both market and technology incumbents will mirror the system-level architectural integration; and 2) the moderating role of incumbent experiences on this baseline relationship. The unit of analysis is the technology component-firm-year, indicating the unit of component-specific knowledge a firm has searched in a given year. I use the OLS estimation with standard errors clustered around firms:

$$Y_{kit} = \alpha + \beta_1(ERA2_{kit}) + \beta_2\,(LIGHT_{Kit}) + \beta_3\,(ERA2_{kit} \times LIGHT_{kit}) + \beta_4(X_{it-1}) + \beta_5(C_{kt}) + \gamma_k + \delta_t + \epsilon_{it};$$

where γ_k and δ_t represent each of 37 technology component- (i.e., substrates, bonding, etc.) and year- fixed effects. Dependent variable, Y_{kit}, equals the interdependence level of the focal technology component k of patents filed by firm i in year t, indicating how much the focal knowledge is integrated with other knowledge. I used three different measures of the interdependence level of the focal component, Y_{kit}. The first measure captures the direct dependencies, while the second and third measures capture both the indirect and direct dependencies. First, the total direct dependencies are equal to the logarithm of the number of both out-degree and in-degree direct dependencies (TOT_DD) with the focal component (MacCormack, Rusnak, and Baldwin, 2007). Empirically, this means the sum of forward and backward citations to the focal component knowledge. In order to capture citations made by firms, I excluded the citations independently added by patent examiners. Similarly to the industry-level propagation cost (Appendix B), I calculated the propagation cost for the focal component for each firm in two ways. The second measure of interdependence, Y_{kit}, is equal to the Visibility Fan In (VFI), the out-degree *indirect* dependencies, defined as the total number of components that cite the focal component k in year t divided by the maximum possible dependencies it can have with other components in an LED system (i.e., 37 = the number of components of the LED technology system at Level1) (Baldwin, MacCormack, and Rusnak, 2014). The third measure of interdependence level, Y_{kit}, is equal to the Visibility Fan Out (VFO), the in-degree *indirect* dependencies, defined as the total number of components that the focal component k cites in year t divided by the maximum possible dependencies with other components in an LED system (i.e., 37) (Baldwin, MacCormack, and Rusnak, 2014). For VFI and VFO, I finally multiplied them by the weights of each component knowledge a firm i searches in year t, equal to 1 – (the counts of focal component patents) / (the total number of patents by firm in year t). The latter two measures respectively depict the *direction* of dependencies associated with the focal component, and are measured in percentages. For example, if it is equal to 5%, the change made to the focal component will propagate influence onto 5% of the total number of components in a system in a given year: thus, the higher the cost, the higher the interdependence.

$\mathrm{ERA2}_{\mathrm{kit}}$ equals one when the patent by firm i is filed after the breakthrough invention during 1993-2006 and zero when it is from 1981-1992. $\mathrm{LIGHT}_{\mathrm{kit}}$ equals one when the patent belongs to a lighting firm and zero when it belongs to a semiconductor firm. I also included time-varying firm and technology component level controls. $X_{i\ t-1}$ is sale of firm i at t-1. C_{kt} equals the total number of patents filed in component k in year t.

Results

Tables 3.1-2 present summary statistics and pairwise correlations. Correlations between the main variables in question are significant at 5%, giving initial clues to go into the regression analysis. Tables 3.3 and 3.4 present the estimates from the OLS regression. In Table 3.3, I included the pre-entry experience variable, LIGHT, and in Table 3.4, SEMICON. In Table 3.3, Model 1 and 2 take the total direct dependencies of the focal technology component of the firm as the dependent variable. Models 3 and 4 take the VFI, indirect outward dependencies; Models 5 and 6 take the VFO, indirect inward dependencies, as the dependent variable. Models 1, 3 and 5 are the estimation results excluding technology component- and year- fixed effects. R squared increases in size after adding two fixed effects in Model 2, 4, and 6, suggesting that fixed effects do add explanatory power. Controlling for technology component- and year-fixed effects, I find that in Table 3.3, the coefficient on ERA2 is significant and positive at 5% and 1% level across all models, giving strong support for the mirroring hypothesis for semiconductor firms (when LIGHT = 0). This result indicates that the interdependence level of technology components semiconductor firms search increases during the era of integration. In fact, the predicted value shows that the average interdependence level has risen 29.9% from the era of modularity to the era of integration, in terms of total direct dependencies. For indirect dependencies, there was an increase of about 1.2% in terms of VFI and of 0.89% in terms of VFO from the era of modularity to the era of integration for semiconductor firms. In Table 3.4, I coded the incumbent variable as SEMICON so that I can capture the effect of moving to the era of integration for lighting firms. I find that the coefficient on ERA2 is significant at 5% for lighting firms only for the total direct dependency model (when SEMICON = 0). Thus my hypothesis 1, the "mirroring hypothesis" is more strongly supported for semiconductor firms than for lighting firms.

In Table 3.3, the coefficient on LIGHT is positive and significant at 5% and 1% in Models 2 and 4. This result indicates that the interdependence level of technology components that lighting firms search *during the era of modularity* (when ERA2 = 0) is in fact higher than that of semiconductor firms. The coefficient on SEMICON in Table 3.4 is negative and significant at 1% supports this result in a mirror image. In the above section, I did not hypothesize specifically about the differences in search behaviors of two incumbent firms during the phase before the watershed event. But I found that during this era of modularity, lighting firms engage in more integrative search than do semiconductor firms.

Lastly, the coefficient on the interaction term, ERA2XLIGHT, is negative and significant at 5% in Model 2, suggesting that the increase in the interdependence level from the era of modularity to the era of integration is significantly less for lighting firms in terms of total direct dependencies. In other words, the extent of the increase of integration across the technology components moving from the era of modularity to the era of integration, or the extent of “mirroring,” is significantly less for lighting firms than for semiconductor firms, giving support for Hypothesis 2. Overall, the results indicate that, nearing commercialization, the extent to which firms engage in integrative search depends on their core capabilities. The ability to engage in more integrative search is more pronounced for semiconductor firms that possess technological incumbency than for lighting firms that possess market incumbency. Therefore, as the literature has predicted, (market) incumbents do adapt less to the changing technological environment, even in terms of knowledge integration (Henderson and Clark, 1990).

Table 3.1 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
TOT_DD	11470	0.241	0.622	0	3.583
VFI	11470	0.011	0.040	0	0.486
VFO	11470	0.009	0.045	0	0.609
ERA2	11470	0.964	0.185	0	1
LIGHT	11470	0.158	0.364	0	1
ERA2XLIGHT	11470	0.145	0.352	0	1
COUNT COMPO	11470	67.520	139.891	0	973

Table 3.2 Correlation matrix

	TOT_DD	VFI	VFO	ERA2	LIGHT	LIGHT xERA2	COUNT COMPO	US
TOT_DD	1							
VFI	0.753*	1						
VFO	0.655*	0.584*	1					
ERA2	0.052*	0.047*	0.037*	1				
LIGHT	-0.027*	-0.045*	-0.037*	-0.108*	1			
ERA2XLIGHT	-0.020*	-0.038*	-0.032*	0.079*	0.951*	1		
COUNT COMPO	0.390*	0.194*	0.175*	0.076*	-0.028*	-0.014*	1	
US	-0.022*	-0.009*	-0.017*	-0.061*	-0.257*	-0.253*	-0.019*	1

*Correlation significant at 5%.

Table 3.3 OLS estimation for the technology interdependence

	Model 1 TOT_DD	Model 2 TOT_DD	Model 3 VFI	Model 4 VFI	Model 5 VFO	Model 6 VFO
ERA2	0.0883***	0.299***	0.00746***	0.0120**	0.00569**	0.00890**
	(0.0312)	(0.0848)	(0.00283)	(0.00486)	(0.00228)	(0.00423)
LIGHT	0.0556**	0.0934***	0.000930	0.00252**	-0.000128	0.00145
	(0.0270)	(0.0117)	(0.00119)	(0.00112)	(0.00137)	(0.00140)
ERA2XLIGHT	-0.0723	-0.111**	-0.00484	-0.00607*	-0.00383	-0.00519
	(0.0519)	(0.0516)	(0.00348)	(0.00364)	(0.00313)	(0.00348)
SALE	0.000673	0.000661	0.000209	0.000379	0.000510	0.000669
	(0.0108)	(0.0111)	(0.000822)	(0.000854)	(0.000755)	(0.000788)
COUNT	0.00172***	0.000529**	5.38e-05***	3.40e-05***	5.63e-05***	4.93e-05*
COMPO	(0.000189)	(0.000214)	(1.02e-05)	(1.25e-05)	(1.53e-05)	(2.41e-05)
Constant	0.0279	-0.154*	-0.00104	-0.00388	-0.00302	-0.00995*
	(0.0577)	(0.0822)	(0.00437)	(0.00647)	(0.00407)	(0.00574)
COMPONENT	-	YES	-	YES	-	YES
YEAR	-	YES	-	YES	-	YES
Observations	11,100	11,100	11,100	11,100	11,100	11,100
R-squared	0.158	0.226	0.040	0.091	0.035	0.069

Notes. Clustered errors (around firms) in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Models (2), (4), (6) include component- and year- fixed effects.

Table 3.4 OLS estimation for the technology interdependence

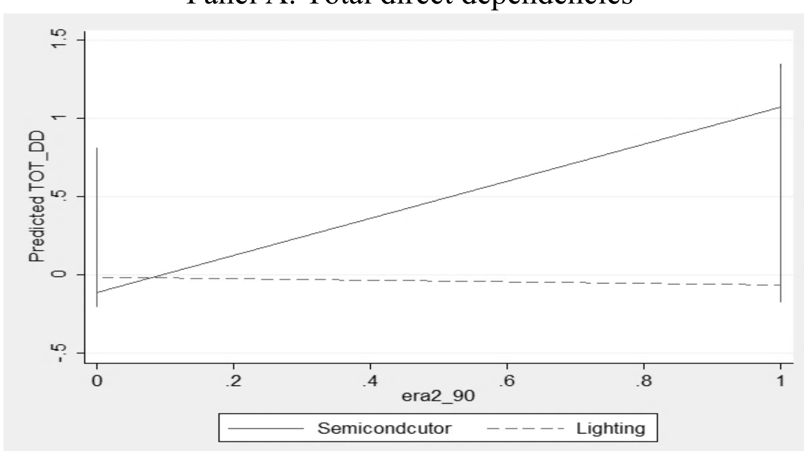
	Model 1 **TOT_DD**	**Model 2** **TOT_DD**	**Model 3** **VFI**	**Model 4** **VFI**	**Model 5** **VFO**	**Model 6** **VFO**
ERA2	0.0160	0.189**	0.00262	0.00596	0.00186	0.00371
	(0.0404)	(0.0807)	(0.00187)	(0.00462)	(0.00175)	(0.00425)
SEMICON	-0.0556**	-0.0934***	-0.000930	-0.00252**	0.000128	-0.00145
	(0.0270)	(0.0117)	(0.00119)	(0.00112)	(0.00137)	(0.00140)
ERA2XSEMICON	0.0723	0.111**	0.00484	0.00607*	0.00383	0.00519
	(0.0519)	(0.0516)	(0.00348)	(0.00364)	(0.00313)	(0.00348)
SALE	0.000673	0.000661	0.000209	0.000379	0.000510	0.000669
	(0.0108)	(0.0111)	(0.000822)	(0.000854)	(0.000755)	(0.000788)
COUNT COMPO	0.00172***	0.000529**	5.38e-05***	3.40e-05***	5.63e-05***	4.93e-05**
	(0.000189)	(0.000214)	(1.02e-05)	(1.25e-05)	(1.53e-05)	(2.41e-05)
Constant	0.0834	-0.0602	-0.000114	-0.00136	-0.00315	-0.00850*
	(0.0724)	(0.0738)	(0.00529)	(0.00585)	(0.00487)	(0.00505)
COMPONENT	-	YES	-	YES	-	YES
YEAR	-	YES	-	YES	-	YES
Observations	11,100	11,100	11,100	11,100	11,100	11,100
R-squared	0.158	0.226	0.040	0.091	0.035	0.069

Notes. Clustered errors (around firms) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Models (2), (4), (6) include component- and year- fixed effects.

In generating the industry-level proposition above, I found that all the components become dependent on every other component several years before the breakthrough invention. The above regression analyses show the results, taking ERA2 as the years following 1993. For robustness checks, I ran the regression again with ERA2 equal to 1 for the years following 1990, 1991, and 1992. The results are consistent with those shown above. Graphical representations of estimated effects are shown in Figure 3.1. I have also tested my hypotheses using the Generalized Linear Models[9]; the results from this model are qualitatively consistent with the OLS model.

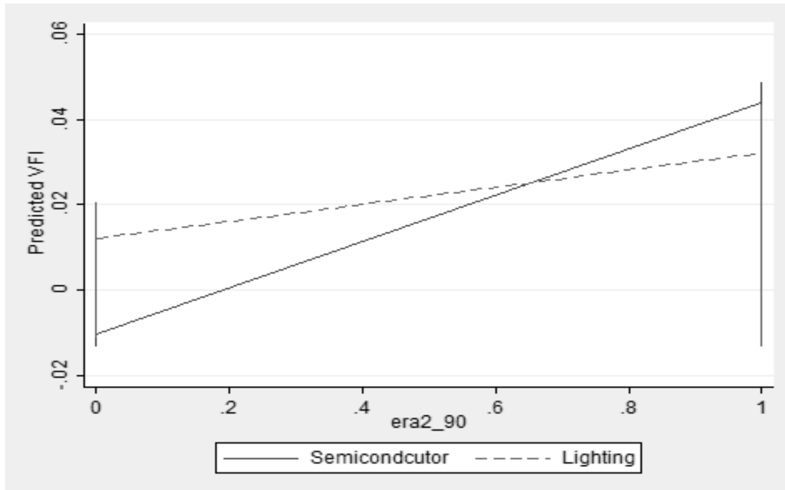
Figure 3.1 Predicted technology interdependence

Panel A. Total direct dependencies

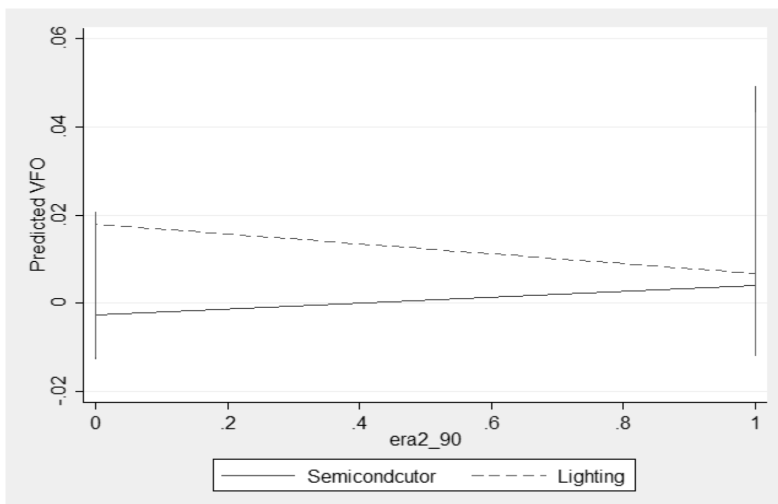


[9] The results can be provided by the author of this dissertation upon request.

Panel B. Visibility Fan In



Panel C. Visibility Fan Out



Discussion and Conclusion

The first purpose of this study is to uncover the evolution of an emerging technology system during the pre-commercialization period, before the inception of a new product market. I build on the insight, drawn from studies of technological changes, that technology architecture will become more integrated as it nears commercialization. In the absence of demand heterogeneity, technological evolution resembles the pattern of scientific advancement. I find that, initially, the knowledge underlying specific components within a system clusters within its own subsystem, and gradually spills over to other subsystems. The innovation landscape, however, then changes, due to the arrival of a breakthrough invention. In solid-state lighting, the technological search started in the core semiconductor technology, which created the new light source and eventually led to the Shuji Nakamura's Nobel Prize-winning invention of the blue LED in 1993. After this event, the inventive efforts in complementary technologies to make better LED light took off, resulting in the integration of knowledge across the core and complementary technology subsystems.

The second purpose of this study is to uncover the search strategies of firms vis-à-vis the pre-commercialization technology evolution theorized above. I focus on explaining the different ways that two types of incumbents, namely market and technology incumbents, design their search strategies. The solid-state lighting industry provides an ideal setting to explore this question, because two giant groups of established firms converge to enable the LED light revolution. In solid-state lighting, lighting firms possess downstream capabilities to integrate different lighting components into an end product as well as the knowledge about consumers. On the other hand, semiconductor firms caused the disruption by their core capabilities in semiconductor-based LED light, but lack knowledge about lighting.

Using the analogy from the mirroring hypothesis, I argue that both incumbents will mirror the evolution unfolding at the system level, and engage in an architectural innovation rather than modular innovation over the pre-commercialization life cycle. A more interesting phenomenon I unpack is the effect of incumbent experiences on the degree to which firms engage in an integrative search, or the extent to which they would "mirror" evolving technology architecture. As the potential of LED usage in general illumination becomes apparent with the Nakamura invention, both types of incumbents engage in efforts to make an LED lighting product, such as a light bulb. I argue that during this latter phase, the era of integration, lighting firms that possess downstream capabilities will experience less uncertainty than semiconductor firms in terms of introducing LED lighting products. Hence, I argue that lighting firms will mirror a system-level architectural integration to a lesser degree than do semiconductor firms. From the parametric analysis, I find strong support for both the baseline mirroring prediction and the moderating role of incumbent experiences on firms' design choices.

I make two important contributions to the literature. First, as I endogenize the arrival of a technological breakthrough, I provide an explanation for the mechanisms leading to architectural integration during the pre-commercialization life cycle. In so doing, I illustrate the different innovation challenges present before and after the breakthrough invention. As a result, I highlight that a technology journeys through a life cycle during the pre-commercialization phase.

Second, I study the role of incumbent firms in shaping the architectural evolution of an emerging industry. I find that both market and technology incumbents indeed invest heavily in an emerging technology system in the anticipation of a new product market. Yet there is significant variance in how they search for new knowledge, specifically in the way they integrate diverse component knowledge. This suggests that even if two types of incumbents search for the same component knowledge in a given year, one group might focus on deepening that component knowledge while the other group might integrate other component knowledge into supplementing focal knowledge. Such integrating behavior is found to be more pronounced for technology incumbents, especially after it becomes evident that their own technology will be commercialized in a new product market. This study therefore contributes to the pre-entry experience literature by showing that the heterogeneity *within* the incumbent experiences impacts firms' initial technological search in the context of industry emergence.

CHAPTER 4

PRE-COMMERCIALIZATION KNOWLEDGE INTEGRATION AND PRODUCT PERFORMANCE

Introduction

A key insight from evolutionary research is that firms' strategic decisions and performance are path-dependent (Nelson and Winter, 1982; March, 1991). In this regard, scholars increasingly argue that the technological choices firms make during the pre-commercialization period are consequential for their subsequent performance (Eggers, 2014; Moeen and Agarwal, 2016). The pre-commercialization investments in emerging technologies benefit firms by allowing them to accumulate relevant experience and knowledge, given that the associated costs of making some irreversible choices do not exponentially hurt the overall outcome (Eggers, 2014; Henderson and Clark, 1990; Mitchell, 1991). This line of research suggests that firms may differ in their ability to translate pre-commercialization knowledge into post-market performance.

Given that the pre-commercialization period has its own life cycle, firms take different evolutionary paths to commercialization, and these different experiences will have an impact on post-commercialization performance. An evolutionary perspective suggests that industry evolution goes through a dynamic process between firms' creation of capabilities and the evolution of environmental conditions, and the firms that perform well and survive are those that adapt to the changing environment (Aggarwal and Wu, 2014; Agarwal, Sarkar, and Echambadi, 2002; Nelson and Winter, 1982; Suarez and Utterback, 1995; Weigelt and Sarkar, 2012). I argue that firms adapt their strategic behaviors along the pre-commercialization life cycle in addition to doing so post-market formation. During the pre-commercialization phase, such adaptive behaviors are reflected in the ways firms search for new technological knowledge vis-à-vis the technology evolution that precedes a market inception.

The core idea is that upon making technological entries into the pre-commercialization period (Cattani, 2005; Malerba and Orsenigo, 1999), firms will employ search strategies, which will be different in the degree to which the multiple component knowledge of a nascent technology system is integrated. This recombinative activity underscores the essence of product innovation: integrating disparate knowledge elements into valuable new combinations (Grant, 1996; Kogut and Zander, 1992). In this respect, scholars have articulated the benefits of knowledge integration rather than modularization on innovation performance. For example, knowledge integration acts as an alternative mechanism to a hierarchical coordination of commercialization activities in the face of a technological change (Kapoor and Adner, 2011). Also, investing in the knowledge of outsourced components helps a firm foster better communication and execute better contracts with suppliers (Tiwana and Keil, 2007). I focus on a learning mechanism that pre-commercialization knowledge integration enables and which translates into post-market performance: this period allows a firm to experiment with nascent technology architecture and to make sense of an emerging dependency structure of components that form a new product. In the context of my study, firms explore different LED components that go into making a new solid-state lighting product. Such experimental search becomes highly important, especially after the breakthrough invention that makes certain a new market application of the LED technology. The benefits from pre-commercialization knowledge integration become evident when a firm develops the system-level knowledge about a coming product by trying out the interdependence between various components. I argue that, when a market takes shape, firms that make linkages between the components and thereby develop the knowledge of an LED lighting system will perform better than those that master component knowledge.

In this study, I measure firms' innovation performance as their products' performance, as opposed to mortality (e.g., Carroll *et al*., 1996) or time-to-market (e.g., Kapoor and Adner, 2011). I base this measurement on the findings from recent research relating pre-commercialization experience to product performance (e.g., Eggers, 2014), and also those relating firms' search efforts to the creation of new products (e.g., Katila and Ahuja, 2002). Furthermore, the modularity research presents ample evidence that firms' pursuing an integral over modular product architecture results in different product performance (Baldwin and Clark, 2000; Ulrich, 1995). As such, linking pre-commercialization technological search to initial product performance also has significant managerial relevance as firms strive to place a foothold in an emerging industry.

However, the benefit of pre-commercialization knowledge integration is not uniformly distributed across firms. Instead, they depend on the experiences and capabilities firms have accumulated in a prior market. Notwithstanding the recent call that we need a richer understanding of the heterogeneity across the experiences of diversifying entrants (Benner and Tripsas, 2012), the effect of their prior industry experience on a new market performance is limited. By definition, potential diversifying entrants have been operating in one or more value chains during the pre-commercialization period of an industry. In this respect, I highlight how post-market performance depends on the position firms have occupied along previous value chains: they can make a vertical or a horizontal entry. Vertical entrants are a group of firms that had been situated at the upstream end of a prior industry value chain (e.g., phosphors firms). By contrast, horizontal entrants are a group of firms that had been situated at the downstream end of a prior industry value chain (e.g., computer firms). The former group of firms had been operating as component makers and served system integrators while the latter group had been operating as system integrators and served the end-market customers. In this chapter, I predict that the value of pre-commercialization knowledge integration is contingent upon the type of entry into a new industry.

While vertical entrants can be experts in the component knowledge, they lack a so-called "integrative capability" needed to commercialize an end-market product, which involves a holistic experience in manufacturing, distribution and marketing (Grant, 1996; Helfat and Raubitschek, 2000; Iansiti and Clark, 1994). In the absence of integrative capability, knowledge integration will act as an alternative mechanism that can help firms coordinate the final product development tasks. In other words, the marginal benefits firms can achieve from integrating knowledge are greater for vertical than for horizontal entrants. Vertical entrants' accumulative efforts to understand new technology architecture during the pre-commercialization phase will later help them understand the process of integrating materials and components into manufacturing a final product, i.e., a light bulb. On the other hand, while the horizontal entrants maintain the benefits of knowledge integration, the extent to which they reap value from it is less than it is for vertical entrants.

Using the sample of publicly-traded firms that have filed at least one solid-state lighting product with the Department of Energy-sponsored Lighting Facts database between 2009 and 2013, I find strong support for the baseline hypothesis that pre-commercialization knowledge integration benefits firms in terms of initial product performance in a new solid-state lighting market. On the other hand, I did not find support for the moderating hypothesis that the positive effect of knowledge integration on firm performance is greater for vertical entrants than for horizontal entrants. Surprisingly, I found instead that horizontal entrants with pre-entry integrative capability realize a greater benefit from pre-commercialization knowledge integration than vertical entrants; in a certain dimension of product performance, experience triumphs knowledge.

To probe this finding more deeply, I used a different performance metric, namely "color accuracy," which defines quality light color rather than mere light output, which I had previously used as my dependent variable. Understanding this dimension of performance allows for a stronger understanding of the lighting market, and I found support for the moderating hypothesis that vertical entrants in this context enjoy greater benefits of knowledge integration than horizontal entrants based on this metric. This result implies that entrants can mitigate the trade-off inherent in the different performance metrics that they need to deliver in a nascent market by leveraging pre-commercialization knowledge. The results hold after controlling for the selection bias that can be present in a sample of firms deciding to launch lighting products in a new solid-state lighting market.

This study makes two primary contributions. First, I add to the recent studies examining the idiosyncratic paths firms take to commercialization (Eggers, 2012b; Eggers, 2014; Moeen, 2013) by highlighting that *how* firms design their search strategies along the pre-commercialization life cycle has important bearings on their post-market performance. This study therefore supplements the existing industry evolution literature, which studies the entry, survival, and adaptive capabilities of firms during the post-commercialization life cycle (e.g., Agarwal, Sarkar, and Echambadi, 2002; Bayus and Agarwal, 2007; Gort and Klepper, 1982; Agarwal and Bayus, 2002), by investigating developments in the pre-commercialization life cycle. Second, I add to the pre-entry experience literature by highlighting the heterogeneity within established organizations in the way they search for new technological opportunities even before a market emerges. The creative destruction literature usually starts with the instance of product commercialization and tracks the dynamics between *de alio* and *de novo* entrants over time. I contend that *de alio* entrants' heterogeneous pre-entry capabilities are equally important and merit further scholarly scrutiny. In this spirit, I distinguish the experience of system integrators from component makers and discover differential performance implications. The results from this chapter highlight that post-commercialization strategic differences are indeed attributable to firms' pre-commercialization knowledge and experience.

Theory and Hypotheses

Diversifying Entrants

Firms that enter a nascent market with some type of past experience are known as "diversifying entrants" or "*de alio* entrants" in the literature. They have relatively little organizational inertia compared with market incumbents (Henderson and Clark, 1990), but have the necessary assets to complement their capabilities in contrast to *de novo* entrants (Prahalad and Hamel, 1994; Teece, 1986). Therefore, ample studies point to diversifying entrants' competitive advantage relative to other types of entrants (Carroll *et al*., Ganco and Agarwal, 2009; Helfat and Lieberman, 2002; Klepper and Simons, 2000; Mitchell, 1991). Among those, the most prolific are comparisons of *de alio* and *de novo* strategies and performance.

However, the way that firms leverage their pre-entry experiences into post-market performance can still vary, even when they all have pre-entry capabilities (Franco *et al*., 2009). The primary focus in the literature has turned to identifying "whether firms enter, when they enter, and whether they survive" (Benner and Tripsas, 2012) in a new industry. The lack of understanding of alternative post-entry variance is surprising, given the vast empirical evidence of various types of *de alio* entrants comprising a new industry (Carroll *et al.*, 1996). Aside from predicting different post-entry performances within a group of diversifying entrants, not many studies provide theoretical and empirical accounts of how they develop pre-commercialization capabilities. There are a few studies that find examples of the effect of pre-entry experiences on post-entry performance. Benner and Tripsas (2012) illustrate that firms with the same prior affiliations would launch a similar set of product features. Also, Eggers (2014) notes that having invested in the losing technology before entry, even when it does not become a dominant technology, helps firms perform in a new industry. As such, firms' experiences during the pre-commercialization period result in varying commercialization activities and performance. In the LED industry, more than a decade passed between the advent of the blue LED and the instance of the first LED product. It is a misconception that firms would start to accumulate knowledge in solid-state lighting only after witnessing an LED light bulb on the market. Instead, firms would be keen to develop knowledge in a radical technology that is highly commercializable, and eventually a select group of firms would make market entries with such prior knowledge. In this chapter, I look into the pre-commercialization heterogeneity within a group of diversifying entrants in terms of how they search for and integrate the knowledge of an emerging technology system, and make predictions about their post-market performance.

Knowledge Integration and Product Performance

Developing a new product entails accumulating both component and architectural knowledge (Henderson and Clark, 1990). In this regard, the benefits from knowledge integration are well established in the literature. Kapoor and Adner (2011) illustrate that firms outsourcing component manufacturing can gain an advantage by investing in the component knowledge, in terms of shortening the period to commercialization. Iansiti (1994) finds that the differences in market performance are in fact attributable to the extent of technology integration even before the product design stage. Those high-performing projects focused on developing system-level knowledge by considering the "systemic impact of novel technical concepts" (522). The modularity literature also documents how engineers' goals affect their commitment to product architecture. For example, engineers design an integrative product architecture when pursuing performance maximization and conversely a modular architecture when pursuing flexibility (Sosa *et al.*, 2005). This makes clear that developing an integrative design is especially important when meeting the functional requirements of a new product (Ulrich, 1995). These findings thus imply that knowledge integration is likely to result in better-quality products in the market. Given the premise that understanding a new technical design requires a sufficient amount of exploration, pre-commercialization knowledge integration will help firms understand an emerging technology architecture before a complete interface emerges.

Understanding the architectural properties of a new technology is especially crucial for diversifying entrants because they are prone to failing to leverage their prior R&D (Henderson, 1993; Henderson and Clark, 1990). Simply possessing a pool of related knowledge (Cattani, 2005; Carroll *et al.*, 1996) does not necessarily mean an effective application of it. By engaging in an integrative search during the pre-commercialization period—that is, by exploring the different component knowledge *and* learning linkages across components—established organizations learn the unfamiliar dependence structure of an emerging technology system. And by knowing more of it, firms are more likely to successfully translate that knowledge into products. In solid-state lighting, a technological discontinuity springs from a semiconductor-based LED light source, and other complementary technologies such as thermal controls develop around this core subsystem to complete LED lighting architecture. By making linkages between different knowledge components, a firm accumulates knowledge not only about the LED diodes, but also how other components connect to the diodes to produce quality light output. In experimenting with the various technical interfaces underlying those components (Henderson and Clark, 1990), firms are able to consistently update their expectations of technological progression (Eggers, 2012a). Such capability is accumulative and path-dependent. And if firms remained the masters of modular knowledge before a new market emerged, they would lag behind in a competitive learning race to establish nascent market presence. Launching a new generation of products with high performance parameters will help diversifying entrants establish an initial competitive advantage in a nascent market. I argue that knowledge integration after the technological breakthrough, or during the era of integration, helps firms develop quality products in the infant years of a nascent industry. Therefore, as a baseline prediction:

> *Hypothesis 1: The greater the degree of knowledge integration during the pre-commercialization period, the better the product performance in the early years of the post-commercialization period.*

The Moderating Role of Pre-Entry Experience

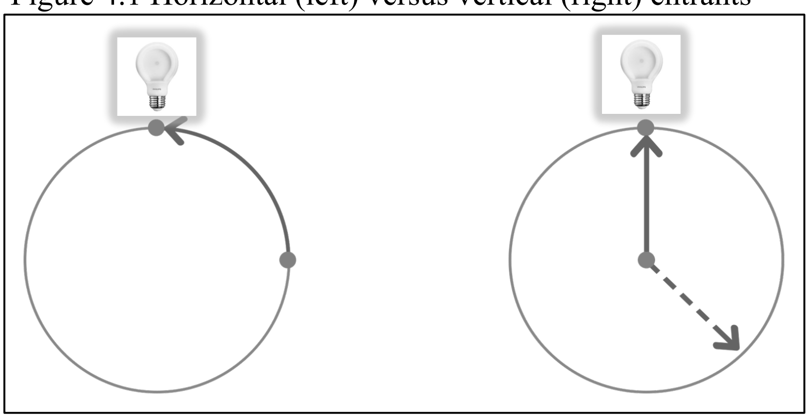
Diversifying entrants can be differentiated in terms of their ability to enter a new market. In her theoretical framework, Sosa (2013) shows that as established firms enter an emerging technological field with different resource bases and capabilities, the traditional understanding of the net positive effect of "related" pre-entry experiences on performance (e.g., Klepper & Simons, 2000) fails to explain the heterogeneity within a group of *de alio* entrants who have entered exactly because their capabilities are aligned with those required for a new industry. Studying the variance in pre-entry capabilities is important because the extent to which firms can leverage their experience and knowledge depends on their existing capabilities and resources (Benner and Tripsas, 2012; Helfat and Lieberman, 2002; Kapoor and Furr, 2014; Lahiri and Narayanan, 2013; Sosa, 2011;

Wu, Wan, and Levinthal, 2014). In this section, I explore the contingent role entrants' pre-entry capabilities play in the relationship between knowledge integration and performance.

Two distinct groups of firms make their entries into a nascent industry: horizontal and vertical diversifiers (Barnett and Burgelman, 1996; Carroll *et al.*, 1996). I define and categorize these two groups based on their positions in a prior value chain (Carroll *et al.*, 1996; Helfat and Eisenhardt, 2004), which indicates whether they possess an "integrative capability." High-performing firms possess a high-order capability to integrate different specialist knowledge within a firm (Grant, 1996; Kogut and Zander, 1992). Horizontal diversifiers have experience performing as system integrators in their prior markets, and are positioned at the downstream end of a prior value chain (See Figure 4.1). Not only do they possess the necessary complementary assets for production and distribution, but more importantly, they have prior experience in integrating materials and components into an end product (Adner and Kapoor, 2010). These firms have developed idiosyncratic organizational mechanisms to facilitate the integration of components (Helfat and Raubitschek, 2000). Such mechanisms are elements like intra-organizational communication channels across teams (Henderson and Clark, 1990), and ways to share and transfer diverse knowledge within a firm (Zander and Kogut, 1995). Photography firms entering the digital camera industry (Benner and Tripsas, 2012), carriage manufacturers entering the automobile industry (Carroll *et al.*, 1996) and computer industry firms entering flat panel displays (Eggers, 2012a) are a few examples of horizontal diversifiers entering an emerging industry.

On the other hand, vertical entrants are firms that act as component suppliers in their original markets and that are positioned at the upstream end of a prior value chain. An example from this study is that of semiconductor firms such as Cree making an entry into an emerging solid-state lighting market. Unlike horizontal entrants, vertical entrants lack the capability to integrate various materials and components along a value chain into an end product. These vertical entrants face a double challenge in a nascent market; they must not only acquire complementary assets to enable the production of new goods but must also learn to address the needs of end consumers. In this regard, vertical entrants (although they may possess required technological experience (Nerkar and Roberts, 2004) that is directly deployable in a new industry) are at a critical disadvantage relative to horizontal entrants because they do not possess integrative capabilities.

Figure 4.1 Horizontal (left) versus vertical (right) entrants



Pre-commercialization knowledge integration will in this context act as a mechanism "mediat[ing] between R&D and development activities" for vertical entrants (Iansiti, 1997: 346). The benefits of the pre-commercialization knowledge integration come from having an opportunity to accumulate knowledge of different components and their linkages. When a diversifying entrant makes a vertical product expansion (Helfat and Raubitschek, 2000), it will take advantage of pre-entry knowledge exploration. This is because for them, developing the system (i.e., a whole value chain) knowledge during the pre-commercialization period will serve as substitute for the integrative capability component makers lack (Nerkar and Roberts, 2004). Horizontal entrants, on the other hand, already possess the capacity to work with participants in an entire value chain. The literature finds that adding additional external knowledge, such as through alliances to an already rich knowledge base, may increase the complexity of coordinating different activities within a firm (Lahiri and Narayanan, 2013). Even if horizontal entrants do not develop and integrate pre-commercialization knowledge, they have the inherent capability to incorporate new knowledge to enable product innovation (Iansiti, 1997). While the variance within this group of firms is determined by the extent to which they have invested in pre-commercialization knowledge (Eggers, 2014), they will enjoy less benefit from pre-commercialization knowledge than will vertical entrants in terms of making quality products when they do actually integrate the knowledge. Hence, the benefits from pre-commercialization knowledge integration on innovation performance will be greater for vertical entrants than for horizontal entrants.

Hypothesis 2: The positive relationship between the degree of knowledge integration and product performance will be moderated by type of entrant such that the relationship will be stronger for vertical entrants than for horizontal entrants.

Data

In this chapter, I have two sample groups of solid-state lighting firms. The first group includes a sample of 1,070 publicly-traded for-profit firms that have filed at least two solid-state lighting technology patents between 1981 and 2012. I use this initial risk set of firms to address the potential selection issue related to the unobserved heterogeneity of firms that have eventually made market entries into the solid-state lighting industry. For instance, vertical entrants that entered the solid-state lighting market can be virtually high-performing firms that can make higher quality products. The second sample used in the main analysis includes 31 publicly traded for-profit firms that have registered at least one solid-state lighting product with the Department of Energy-sponsored Lighting Facts Program, the source of the entrants' performance data used in this study, between 2009 and 2013 (http://www.lightingfacts.com). I chose to use the Lighting Facts product database for this study for two reasons. Given that the solid-state lighting market is at the initial stage of development, the Department of Energy has made it an initiative to raise consumer awareness of new, solid-state lighting products. Forging partnerships with this program requires firms to report their LED product performance metrics in accordance with an industry standard. When registered with the Lighting Facts program, a firm can place a Lighting Facts label on its LED lighting products. This dataset therefore precludes the inclusion of false information associated with the usually unreliable source of infant products in a nascent industry. With Department of Energy partnership labels on products, manufacturers gain reliability in the market. The second reason is that there is still significant variance across 1) the types of products firms market, e.g., lamps versus luminaires, and 2) the quality of products associated with the Lighting Facts program. The products in the database are reported with five different performance metrics approved by the independent labs. The unit of analysis in the main model is therefore the product-firm-year.

Measures

Dependent variable: I focus on a measure that can capture the post-market performance of firms that searched for new technological knowledge during the pre-commercialization period. In conjunction with recent studies relating pre-commercialization experience to product performance (e.g., Eggers, 2014) and also those relating firms' search efforts to the creation of new products (e.g., Katila and Ahuja, 2002), I take the product performance of firms as an indication of innovation outcome. I measured the firm i's product p's performance at time t (PROD_PERF_p, i, t) with a main light performance parameter called lumens per watt (lm/w) indicating light efficacy. This measure is used in the industry to compare LEDs' competitive parity with conventional lighting technologies. In order to achieve high efficacy values, firms need to excel in a variety of dimensions. For example, this requires an understanding of the electrical work in addition to the ample generation of white light from the LED source.

Independent variables: The degree of pre-commercialization knowledge integration (PRECOM INT_i, 1993-2006) of firm i is measured by what is called the *propagation cost* used in the modularity literature (Baldwin, MacCormack, and Rusnak, 2014; MacCormack, Rusnak, and Baldwin, 2006). First, I created the Design Structure Matrix (DSM) according to the steps defined in chapters 2 and 3 between 1993 and 2006 for each firm in the sample.[10] Visibility Fan In (VFI_i, 1993-2006) and Visibility Fan Out (VFO_i, 1993-2006) will represent the propagation cost of the entire knowledge system of the firm i averaged over 1993-2006. The interdependence between knowledge components (i.e., DSM entries) is again represented by the patent citations. The higher the propagation cost, the greater the degree of knowledge integration a firm i has engaged. The final measure of pre-commercialization knowledge integration is then weighed by the number of patents a firm files in each year. This takes into account that among firms who filed the same number of patents for component knowledge, the level of integration can differ. Examiner citations are excluded in this chapter.

The pre-entry experience of sample firms is coded as VERTICAL_i, 2008 = 1 if a firm is a vertical entrant and 0 if a horizontal entrant. The entry type is determined depending upon the firm i's associated SIC recorded in Compustat database in 2008, a

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[10] As in chapter 3, one DSM represents a firm's knowledge system in a given year.

year prior to its entry into the solid-state lighting market. The distribution of this variable is reported in Table 4.1.

Table 4.1 Vertical vs. horizontal entrants

SIC	Description	Entry type
2670	Converted Paper And Paperboard Products	vertical
3559	Special Industry Machinery, Not Elsewhere Classified	vertical
3571	Electronic Computers	horizontal
3600	Electronic And Other Electrical Equipment And Components, Except Computer Equipment	horizontal
3612	Power, Distribution, and Specialty Transformers	horizontal
3640	Electric Lighting And Wiring Equipment	horizontal
3670	Electronic Components And Accessories	vertical
3674	Semiconductors and Related Devices	vertical
3679	Electronic Components, Not Elsewhere Classified	vertical

Controls: The control variables are included for their effect on product quality, including firm sales (SALE_i, t-1), as large firms are more likely to leverage their complementary assets. I also included the stock of pre-commercialization patents each firm i filed during 1993-2006 (PATCOUNT_i, 1993-2006). US_i, t-1 is coded as 1 if a firm is from the United States and 0 if from all other countries. I included a time-varying PATCOUNT_i, t-1 which is the number of LED patents a firm i has filed in t-1. Also included is a variable, UPSTREAM LED_i equal to one if a firm i has vertically integrated into the upstream LED component during 2009-2013. I also included product-level controls to take away confounding effects related to a specific category of the focal product. It is coded as LAMP_p, t =1 if the focal product p is a lamp and 0 otherwise (luminaires and retrofit kits). Table 4.2 describes the summary statistics of my variables.

Table 4.2 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Prod_entry	1070	0.028	0.166	0	1
Prod_Perf (lm/w)	2321	75.309	19.009	14	131.68
Prod_Perf (CRI)	2318	78.507	7.1583	48	96
Precom integration	2321	0.003	0.005	0	0.018
Vertical	2321	0.320	0.466	0	1
Precom integration x Vertical	2321	0.003	0.005	0	0.018
Sale	2321	7.460	1.927	2.484	12.092
Pat	2321	1.421	1.668	0	4.718
Pat, 93-06	2321	1.163	1.377	0	3.837
Lamp	2321	0.152	0.360	0	1
Light	2321	0.577	0.494	0	1
Upstream LED	2321	0.312	0.463	0	1
US	2321	0.846	0.360	0	1

Analysis

Heckman Selection Model

I first analyzed the potential sample bias affecting a certain group of firms systematically entering my product sample data, PROD_ENTRY, i = 1 or 0 otherwise.

This first stage model predicts the likelihood of a risk set of 1,070 firms entering the second stage product performance model including 31 firms. This model includes the variables used in the main model; in addition, I included the exclusion variable, COUNT_CHEM_i, 1981-1992, which is the number of patents a firm i has filed in the chemistry and materials subsystem during the period 1981-1992, before the breakthrough invention. This pre-breakthrough search is identified in the literature as "pre-adaptation" of the radical technology before it shows the potential to be applied to a new market setting (Cattani, 2005). Also, by including only the patents filed in the core technology subsystem, I take into account research findings that indicate that upstream investment is positively related to product commercialization, but not necessarily to product quality, because the general technology is applicable to other value chains (Eggers, 2012a; Eggers, 2014). I run the first stage Heckman model at the firm-level, predicting the likelihood of post-commercialization entry using the probit model with clustered standard errors around industries (SICs). The results of the first-stage model are reported in Table 4.3.

As predicted, patenting in the LED core technology subsystem before the breakthrough invention is positively related to the likelihood of commercialization. Also, the positive and significant coefficient on the interaction term (Precom integration x Vertical) illustrates that vertical entrants that integrate the knowledge in a greater extent during the pre-commercialization period are more likely to commercialize a product. Then, I calculate an inverse Mills ratio to include it in the product-level second stage model as a control. I run the second, main model using the OLS regression with year-fixed effects. The main sample includes a total of 2,321 product-firm-year observations.

Table 4.3 Heckman probit model

PROD_ENTRY	
Precom integration	26.81
	(20.29)
Vertical	-0.347
	(0.225)
Precom integration x Vertical	116.2***
	(26.98)
Pat, Chem 1982-93	0.0866***
	(0.0224)
Sale	-1.81e-06
	(2.64e-06)
US	-0.171***
	(0.0644)
Constant	-1.960***
	(0.349)
N	1,070

Clustered standard errors around SICs in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results

The results from the main model are reported in Table 4.4. Hypothesis 1 predicts the positive effect of pre-commercialization knowledge integration on subsequent performance. I argue that by accumulating capabilities in integrating the technology components in an emerging system, firms are able to understand an emerging architecture, or the dependency structure between each of the LED components that evolve in respective paths. This effect is strongly supported in the full model (Model 3) by the positive and significant ($p<0.01$) coefficient on pre-commercialization integration. Though I have not hypothesized about the main effect of making a vertical entry, I find that the coefficient on VERTICAL in the main model is positive and significant in Model 3 ($p<0.01$). This result indicates that, on average, those entrants that were component makers in a prior market provide higher quality products. One possible explanation is that given the chosen metric of lumens per watt, which essentially captures light output, those vertical entrants with relevant technological capabilities (e.g. semiconductor firms) may be able to launch LED products that score high on bright light. In hypothesis 2, I predicted the positive moderating role of being a vertical entrant on the relationship between pre-commercialization knowledge integration and product performance. The coefficient on the interaction term, Precom integration x Vertical, is however negative and significant ($p<0.01$), meaning that the positive effect of pre-commercialization knowledge integration on product performance is dampened when an entrant is a vertical

Table 4.4 Effect of knowledge integration on product performance (lm/w) – Year fixed effects

PROD_PERF	Model 1	Model 2	Model 3
Inverse Mills Ratio	2.726	3.324	-7.957**
	(1.682)	(2.637)	(3.335)
Sale	-1.586***	-1.805***	-0.655*
	(0.256)	(0.298)	(0.363)
Pat	3.335***	3.045***	3.756***
	(0.730)	(0.756)	(0.762)
Pat, 1993-2006	-1.170	-0.925	-4.893***
	(0.988)	(1.013)	(1.241)
Lamp	-16.50***	-16.04***	-17.34***
	(1.104)	(1.142)	(1.160)
Light	3.486**	3.610*	13.81***
	(1.689)	(1.976)	(2.708)
Upstream LED	5.969***	5.268**	0.709
	(2.041)	(2.254)	(2.390)
US	1.253	0.0737	-2.325
	(1.357)	(1.594)	(1.643)
Precom integration		291.7	1,275***
		(362.6)	(402.7)
Vertical		-1.805	13.07***
		(2.301)	(3.553)
Precom integration x Vertical			-1,900***
			(347.5)
Constant	76.21***	77.38***	88.76***
	(3.232)	(6.709)	(6.984)
Year	YES	YES	YES
N	2,321	2,321	2,321
R-squared	0.331	0.332	0.341

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

entrant. This result is the opposite of what I had predicted; thus, I could not reject Hypothesis 2 at 5% level. This was a surprising finding, since I expected that vertical entrants would enjoy greater benefits of their pre-commercialization knowledge integration on product performance than would horizontal entrants. The implications of this opposite finding are discussed in the next section. The estimated effects of control variables on performance are as predicted in the literature. The coefficient on LIGHT is positive and significant ($p<0.01$), indicating that products made by lighting firms that are market incumbents perform better, on average, than other firms. The coefficient on SALES was negative and marginally significant, indicating that large firms produce lower quality products in the initial years of a new solid-state lighting market. The coefficient on LAMP is negative and significant ($p<0.01$) across all 3 models conferring the fact that lamps have smaller light output than luminaires that are also used for commercial lighting.

Additional Analysis: Performance Trade-Off

As mentioned above, I could not find support for the enhanced benefit of knowledge integration for vertical entrants. Since multiple aspects of LED light can be measured, I probed how firms' products would score on performance metrics other than the light efficacy measure. During my interviews with several industry experts, I found that lighting and semiconductor firms frame the quality of lighting products differently. For example, semiconductor firms focus on generating ample light output regardless of light color, whereas incumbent lighting firms know the importance of providing compatible dimming solutions, because consumers want them. This conflict reflects a trade-off to satiating different dimensions of what quality light means to consumers. For instance, the high efficacy light bulbs have bright light, but can emit blue light that is unpleasant to human eyes.

I focused on the trade-off firms need to make in terms of advancing efficacy versus bettering light quality. All other things being equal, there is an inherent technical trade-off between generating a high amount of light radiation and producing warmer light. Exemplary metrics that can capture such trade-off are lumens per watt (which was used in the previous regression) and CRI (Color Rending Index). In order to enhance the CRI, which ranges from 0 to 100 %, firms have to increase the “redness” of the LED light, which produces few lumens, hence decreasing the efficacy measure. My conjecture here is that vertical entrants who have little understanding of the required functionality of light, such as affecting ambient mood, will make the trade-off to emphasize light output rather than color quality. Despite this potential pitfall, vertical entrants who integrate the knowledge of an LED architecture can uncover the mechanisms of the effects of such a trade-off. Learning technology architecture during the pre-commercialization period will enable vertical entrants to lessen the trade-off between light output and color quality. And again, the marginal benefits from such integrative knowledge will help vertical entrants more than horizontal entrants who can compensate the lack of pre-commercialization knowledge for “integrative capability”.

Given the concern of potential simultaneity of two product performances, I tested the estimated effect of pre-commercialization knowledge integration on firm performance with the Seemingly Unrelated Regression (SUR), using the two light performance metrics as my new dependent variables. The null hypothesis that two dependent variables are not correlated is rejected at 1% in my regression. The results from the SUR models are reported in Table 4.5.

Models 1-3 have lumens per watt as their dependent variable. And Models 4-6 have CRI as their dependent variable. Pre-commercialization knowledge integration has a positive and significant effect on light efficacy only (Model 3). The effect on color accuracy was significant in Model 5, but disappeared in Model 6 after adding an interaction term. This means that having integrative knowledge of an LED lighting system will on average help firms launch quality products that score higher on the efficacy measure, but not on the color accuracy measure. Therefore, hypothesis 1 is only supported in the SUR model with the same dependent variable used in the above section. Again with the SUR model, the coefficient on the interaction term (Model 3) is negative and significant ($p<0.05$) providing a result consistent with the OLS estimation, but an opposite finding from the predicted direction in Hypothesis 2.

Table 4.5 Effect of knowledge integration on product performance – Seemingly Unrelated Regression

PROD_ PERF	**Model 1** lm/w	**Model 2** lm/w	**Model 3** lm/w	**Model 4** Color	**Model 5** Color	**Model 6** Color
Inverse mills ratio	2.711	3.172	-8.118**	-2.605***	0.693	4.774***
	(1.682)	(2.642)	(3.338)	(0.700)	(1.095)	(1.385)
Sale	-1.594***	-1.820***	-0.667*	0.505***	0.791***	0.373**
	(0.257)	(0.299)	(0.365)	(0.107)	(0.124)	(0.151)
Pat	3.296***	3.010***	3.725***	-1.514***	-1.516***	-1.774***
	(0.731)	(0.757)	(0.763)	(0.305)	(0.313)	(0.317)
Pat, 1993-2006	-1.168	-0.909	-4.887***	-1.225***	-1.683***	-0.245
	(0.989)	(1.014)	(1.242)	(0.412)	(0.420)	(0.515)
Lamp	-16.48***	-16.01***	-17.32***	5.349***	4.851***	5.323***
	(1.104)	(1.142)	(1.160)	(0.459)	(0.473)	(0.481)
Light	3.580**	3.638*	13.85***	-4.167***	-2.392***	-6.085***
	(1.692)	(1.976)	(2.708)	(0.704)	(0.819)	(1.124)
Upstream LED	6.143***	5.511**	0.929	3.122***	1.914**	3.570***
	(2.051)	(2.270)	(2.406)	(0.854)	(0.940)	(0.998)
US	1.204	0.0502	-2.348	1.485***	1.314**	2.181***
	(1.359)	(1.595)	(1.644)	(0.566)	(0.661)	(0.682)
Precom integration		270.4	1,257***		413.9***	57.23
		(363.5)	(403.6)		(150.6)	(167.5)
Vertical		-1.952	12.96***		4.790***	-0.599
		(2.312)	(3.562)		(0.958)	(1.478)
Precom integration x Vertical			-1,904***			688.1***
			(347.5)			(144.2)
Year	YES	YES	YES	YES	YES	YES
Constant	84.22***	85.67***	96.63***	83.05***	71.81***	67.84***
	(3.257)	(6.732)	(6.983)	(1.356)	(2.789)	(2.898)
N	2,318	2,318	2,318	2,318	2,318	2,318
R-squared	0.332	0.333	0.342	0.183	0.192	0.200

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

As found in the above section, the pre-commercialization knowledge integration did not help vertical entrants to a greater extent than it helped horizontal entrants in terms of light output (lm/watt). However, the converse is true in terms of the Color Rendering Index. The estimated coefficient on the interaction term in Model 6 is positive and significant ($p<0.01$). This result implies that the benefit of pre-commercialization knowledge integration is more pronounced for vertical entrants than for horizontal entrants in terms of achieving color accuracy of a lighting product. This latter result is consistent with Hypothesis 2, which predicted the positive moderating role of being a vertical entrant on the relationship between pre-commercialization knowledge integration and product performance. The implication of this finding is discussed in the following section.

Discussion and Conclusion

In this chapter, I explored the effect of firms' pre-commercialization technological search on their subsequent performance. The prior literature has predominantly focused on the different dynamics of *de alio* and *de novo* entrants when discussing post-market industry evolution. Ample studies converge on a theme: to the extent that they have entered a new market, *de alios*, which have pre-organizational history, tend to outperform other groups of firms, because they own complementary assets and related capabilities. I contend that this classification has prevented us from exploring the much more complex dynamics among different kinds of entrants: incumbents who are transitioning to a next generation of products, diversifying entrants who are coming from outside the boundary of the focal industry going through a technological change, and new firms that are born within a nascent market. The focus of this study is to uncover the dynamics between the first two groups of firms, potential "diversifying entrants"[11] into an emerging industry. I first predict the benefit of integrating different knowledge components related to an emerging technology system on subsequent performance for all types of entrants. The predicted results from the OLS regression with year-fixed effects support Hypothesis 1, that pre-commercialization knowledge integration is positively related to firms' product performance. The hypothesis was supported even after controlling for a potential sample bias that is related to the correlation between the unobserved firm-level heterogeneity and the likelihood of entries.

Hypothesis 2 was related to the contingent effect of entrants' pre-entry experiences on the baseline relationship between pre-commercialization knowledge integration and product performance. Here, I introduced a new dimension with respect to an entry into a nascent market: a horizontal versus vertical entry. The first group of firms, entering a new focal market, possesses integrative capabilities they acquired by performing as system integrators in a prior industry. Conversely, the second group of

[11] By definition, market incumbents are not treated as diversifying entrants in the literature and thus often omitted in discussions of diversifying entrants. In this dissertation, I have endogenized the market entries of firms by tracing their activities back to the period preceding the instance of product commercialization. Thus, I have included market incumbents in my sample as potential "entrants" into an emerging market industry. The primary focus was to uncover pre-entry experiences of all the entrants that have pre-entry organizational history (Sosa, 2013).

entrants does not possess integrative capabilities when entering a new focal market, due to their experience as component suppliers in a prior industry. I argued that pre-commercialization knowledge integration can act as a mediating mechanism between upstream R&D and product innovation, such that vertical entrants without previous capability to market an end product to consumers can enjoy greater marginal benefits from knowledge integration than would horizontal entrants who already have such know-how.

Intriguingly, I find an opposite, negative moderating role of being a vertical entrant on the relationship between knowledge integration and performance. In other words, the positive effect of the pre-commercialization knowledge integration on performance is more pronounced in the case of horizontal, not vertical, entrants. I had expected that the relative advantage of pre-commercialization knowledge integration would be accentuated for the component makers who did not have experience with end customers. However, it was in fact the horizontal entrants ("lateral diversifiers" according to Carroll *et al*., 1996) that took advantage of their integrative knowledge. Perhaps overcoming the disadvantages stemming from the lack of pre-entry integrative capability with knowledge integration is more difficult than expected. In this case, knowledge could not triumph experience. Then the question becomes what ways can vertical entrants reap value from the pre-commercialization knowledge integration?

As an additional analysis, I went on to test how firms would perform on different dimensions of product performance. Although the light efficacy measured in terms of lumens per watt is the representative lighting performance metric adopted in the industry, the quality of lighting products is determined in a variety of dimensions. One special feature is that how light can mimic blackbody radiation, or how it can deliver the visible light that interacts best with human eyes. An ultimate goal for any lighting firm is thus to balance efficiency and functionality (Hung and Tsao, 2013). I therefore tested how firms would manage this inherent trade-off between light efficacy and color rendering capability. The correlation between two equations of two performance metrics as separate dependent variables is negative and significant at $p<0.01$. The results from the Seemingly Unrelated Regression illustrate that vertical entrants who previously lack the capability to integrate the upstream and downstream components *do* take more advantage of pre-commercialization knowledge integration relative to horizontal entrants in terms of color accuracy. This result implies that the positive effect of pre-commercialization knowledge integration on color accuracy is more pronounced for vertical entrants than for horizontal entrants, supporting Hypothesis 2. This result implies that vertical entrants who previously lack the capability to understand an end market have accumulated the systematic knowledge about lighting during the pre-commercialization phase. Thus vertical entrants have learned to mitigate the trade-off that exists between maximizing efficiency while achieving good degree of light functionality.

The heterogeneity *within* a group of established organizations was an underexplored topic in the industry evolution literature. Moreover, the effect of such heterogeneous experiences on post-market outcome was rarely studied. I make an important contribution to industry evolution and pre-entry experience literature by showing that diversifying entrants have differential product performances based on the previous capabilities they bring to a new market, a type of experience one can accumulate according to a position in a prior value chain. The extent to which firms can leverage their pre-commercialization knowledge depends on their possessing integrative capabilities, such that value of knowledge integration is enhanced for those without previous integrative capabilities.

Finally, I argue that this line of research could be fruitful if the studies of component makers were given separate attention in the literature. Overall, the underlying assumption in the strategy literature is that frameworks and value-propositions of system integrators could be readily applied to component suppliers who are situated far from end customers. Some research, however, suggests that the innovation challenges experienced by upstream and downstream participants are not the same (Adner and Kapoor, 2010). As shown in this chapter, pre-commercialization knowledge integration was not universally beneficial for component suppliers. More essential was furthering systematic knowledge so that a new product can function better in terms of a performance parameter more important to customers. Whether a firm is a horizontal or vertical entrant, they will invest in knowing emerging technology architecture. However, the extent to which they can exploit this knowledge depends on a type of prior value chain experience.

CHAPTER 5

CONCLUSION

This dissertation is a study of the industry emergence phenomenon. It is especially concerned with a period prior to a new product's "life cycle". Scholars of creative destruction have assumed that incumbent industries face technological breakthrough exogenously. As a result, a technology life cycle was also assumed to begin with the instance of commercialization. In solid-state lighting, though, more than a decade passed between the Nobel Prize-winning invention of the blue LED to the commercialization of the LED light bulb. Why? I explore a "life before a life cycle," or pre-commercialization period, to discover the intricate evolutionary pattern of the early LED technology system. I find that industry evolution began more than two decades before the LED light bulbs appeared in retail stores.

Chapter 2 details the phenomenon of knowledge evolution during the pre-commercialization period at the industry level. By breaking down an LED technology system into subsystems and components, I show that different technology components evolve at different paces. Most importantly, I find that the pre-commercialization period exhibits a distinctive life cycle during which a new technology evolves through stages of development: from the era of modularity to the era of integration. Specifically, pre-commercialization technology evolution goes through an architectural integration defined by the full bi-directional dependence among individual technology components after the advent of a breakthrough invention. In the chapters that follow, I rely on this intriguing finding to examine firms' idiosyncratic paths along such a life cycle.

Chapter 3 studies the search designs of two types of incumbent firms: market incumbents, i.e., lighting firms—masters of Edison bulbs—and technology incumbents, i.e., semiconductor forms—masters of the core LED technology. I find that both firms invest heavily in LED lighting research during the entire phase of pre-commercialization and in so doing "mirror" the evolving technology architecture that gets more integrated nearing commercialization. In this chapter, I highlight the different innovation landscapes born before and after the advent of the blue LEDs, "technological breakthrough" as marked in the previous literature. As a result, lighting firms engage in more modular search, whereas semiconductor firms do the opposite after the breakthrough invention of the blue LED. I attribute such differential adaptive behaviors to the challenge of integrating LEDs into lighting applications and understanding the lighting market, issues less challenging for lighting incumbents than for semiconductor firms.

Chapter 4 finally connects firms' pre-commercialization knowledge search to their product performance. I find that the prior value chain positions do matter in terms of furthering the effect of knowledge integration on post-market performance. I introduce the heterogeneity in types of entry: vertical entries by component makers and horizontal entries by lateral diversifiers. I highlight that vertical entrants coming from the upstream end of another value chain can take advantage of pre-commercialization knowledge integration in terms of balancing the different performance dimensions of new products.

Acquiring systematic knowledge of an entire technology architecture will ultimately unleash the benefits of knowledge integration further for vertical entrants when they try to understand a performance dimension that they can easily ignore but consumers readily care about, such as warm light.

On the methodological front, I (for the first time, to my knowledge), introduce the Design Structure Matrix to map the architecture of an emerging technology system using patent citations. A key advantage not available in other network analysis tools is the ease of detecting the directionality of dependence from one element to another. Further, its visualization can be used to represent any system. In this dissertation, I complement it with parametric analysis to find support for most of my hypotheses.

In sum, I contribute to a growing literature that indicates that pre-commercialization activities have significant bearings on firms' post-market strategic differences. In order to study a pre-commercialization life cycle, I focus by definition only on groups of established organizations that have organizational histories before the inception of an industry. Illustrating the heterogeneity within this group of "diversifying entrants," I argue that firms make different choices in terms of pre-commercialization knowledge exploration. Importantly, these exploratory yet important search designs have significant bearings on product performance when a market takes shape.

The limitation of this research is hence the exclusion of entrepreneurial startups contributing to industry emergence phenomenon. One can more fully capture the dynamics by studying market and technology incumbents, other *de alios* and *de novo* firms journeying across the pre-commercialization life cycle. Despite those advantages, this dissertation employs a single-study setting; and hence generalizations about pre-commercialization strategies have to be made carefully.

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APPENDICES

APPENDIX A. SAMPLE BOOLEAN SEARCH FOR SUBSTRATE PATENT

Title, Abstract, or Claims contains:

(((Gallium OR Ga) WITH (Arsenide OR As OR antimonide OR Sb OR nitride OR N OR phosphide OR P)) OR GaAs OR ((indium OR In) WITH (phosphide OR P)) OR InP OR InGaN OR GaSb OR GaN OR AlGaInP OR ((Silicon OR si) WITH (germanium OR Ge OR carbide OR C)) OR AlGaN OR ((Aluminum OR al OR boron OR B) WITH (nitride OR N)) OR AIN OR (diamond WITH (layer* OR substrate*)) OR SiC OR ZnSe OR ((zinc OR Zn) WITH (Se OR selenide)) OR **...** OR LED OR LEDs) AND Class code = H OR C)

Note: This sample Boolean algorithm used to search LED patents is provided by a technology expert at IP Checkups (www.ipcheckups.com). It is proprietary, and the algorithms for other LED technology components cannot be released. Some parts of the above algorithm are deleted because they are proprietary.

APPENDIX B. DESIGN STRUCTURE MATRIX

- **Structure Matrix**

A Structure Matrix is a square matrix in which the same elements are listed in both rows and columns. Matrix entries represent the dependence by a row element on a column element (i.e., a row element depends on a column element). Hence, if an element A depends on an element B, I put '1' in the row of A and the column of B, i.e., DSM (A, B) = 1), and '0' otherwise. In my context, backward citations are conceptualized as interactions between technology components and thus entered into matrix entries. I also used the strength of interactions rather than the presence of interactions (i.e., 0/1). For example, if an epitaxy patent cites lens patents five times, I put '5' in the row of epitaxy and the column of lens, i.e., DSM (epitaxy, lens) = 5. Accordingly, one DSM represents a snapshot of technology architecture of a given year.

- **Visibility Matrix**

I construct what is called the Visibility Matrix, which is the higher order matrix from the Structure Matrix. It includes the *indirect* in addition to the direct dependencies among the technology components. For example, if an element A depends on an element B, which in turn depends on C, the Visibility Matrix also notes that there is indirect dependence from A to C even though there is no direct path from A to C. For example, in my sample, an epitaxy patent cites a lens patent and not a drivers patent in year 1990. If, however, a lens patent cites a drivers patent, I put '1' in the row of epitaxy and the column of drivers, i.e., DSM (epitaxy, drivers) = 1. For the Visibility Matrix, I used the binary code (i.e., 1/0) instead of the strength of interactions. I have coded what is called the Warshall algorithm in Matlab in order to construct the Visibility Matrix for every year, in which case one DSM represents a snapshot of technology architecture of a given year.

- **Propagation Cost**

In order to capture the interdependence (modularity) level of the system architecture, I use what is called the *propagation cost* (e.g., MacCormack et al., 2006). Propagation cost is calculated as follows: summing across the rows of an element of a Visibility Matrix will give the number of components in a system the row element directly or indirectly depends on. Conversely, summing along the columns of an element will give the number of components that directly or indirectly depend on the column element. Dividing the row sum or the column sum[12] of an element by the matrix dimension and averaging the ratios over all elements in the matrix will give the propagation cost, defined as the percentage of other components that will be affected when a change has been made to a randomly selected component in a system. Hence, the higher the propagation cost, the more integrated a system. In short:

$$\text{propagation cost}_t = \frac{\sum \text{VFI}_{jt}}{37};$$

where Visibility Fan In (VFI) of component j in time t indicates the number of components that cite component j in year t divided by the matrix dimension, 37[13]. At the system level, the propagation cost of year t will represent the average VFIs of 37 components.

[12] By mathematical properties, row and column sums are equivalent in the visibility matrix (Baldwin et. al., 2014).

[13] At Level 2, it becomes 19; at Level 3, it becomes 4.