Understanding Firms' Technology Sourcing Strategy: How is it Related to

Complementary Assets and the Hiring of New Inventors

by

Xiaoshu Bei

Business Administration
Duke University

Date:_______________________
Approved:

___________________________
Sharon Belenzon, Supervisor

___________________________
William Mitchell

___________________________
Wesley M. Cohen

___________________________
Frank T. Rothaermel

___________________________
Sharique Hassan

Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor of Philosophy
in Business Administration in the Graduate School of Duke University

2019

<u>ABSTRACT</u>

Understanding Firms' Technology Sourcing Strategy: How is it Related to

Complementary Assets and the Hiring of New Inventors

by

Xiaoshu Bei

Business Administration
Duke University

Date:_______________________
Approved:

___________________________
Sharon Belenzon, Supervisor

___________________________
William Mitchell

___________________________
Wesley M. Cohen

___________________________
Frank T. Rothaermel

___________________________
Sharique Hassan

An abstract of a dissertation submitted in partial
fulfillment of the requirements for the degree of Doctor of Philosophy in
Business Administration in the Graduate School of Duke University

2019

## Abstract

In the dissertation, I study how the firms' external technology sourcing strategies are related to their position in and the development of their capabilities. The analyses focus on the US manufacturing sectors based on comprehensive survey data or archival data on patenting firms and use regression analysis and causal inference to test a series of hypotheses. The main conclusions include: (1) Firms are more likely to focus on internal innovation if they possess valuable complementary assets (trademarks), but are likely to pursue external technology sourcing when they have the assets and are entering new markets. (2) As firms entering new markets and rely on external innovation, they often make changes and redeploy their existing complementary assets. (3) If they cannot hire from externally (thus cannot obtain the new technology and technical capabilities), they will rely more on external technology sourcing, and mostly through acquisition which brings both new technology and technical capabilities.

# Dedication

I dedicate this dissertation to my parents, Yaoming Bei and Deying Deng.

## Contents

# List of Tables

## List of Figures

## Acknowledgments

I am deeply indebted to my advisors for their continuous support and guidance throughout my Ph.D. studies. I would like to thank Sharon Belenzon, Ashish Arora, Wesley Cohen, William Mitchell, Frank Rothaermel, Sharique Hasan, David Ridley, Luis Rios, Ramon Lecuona Torras, Jonathon Cummings, and everyone else from the Duke Strategy program, for the discussion and providing feedback at each stage of my dissertation and other research projects. I greatly appreciate the helpful comments and suggestions from scholars in the Strategic Management Society and Academy of Management, conference participants in Searle Center Innovation Economics, REER, Smith Entrepreneurship Research Conference, Trans-Atlantic Doctoral Conference, Asia Pacific Innovation Conference, as well as my fellow Ph.D. colleagues. Lastly, I thank my family and friends for their unconditional support and companion throughout my academic endeavor.

# 1. Introduction

My dissertation investigates in the relationship between external technology sourcing and firms' resources and capabilities positions.

External sourcing is a common phenomenon in strategy, that has received lots of attention through a few different theoretical lenses. For example, the Transaction Cost Economics theory (Williamson, 1975, 1985, 1991) studies the make-or-buy decision based on the level of transaction cost that incurs during a transaction. The resource-based view (RBV) (J. Barney, 1991; J. B. Barney, 2001) emphasizes the importance of resources and capabilities in establishing and sustaining firms' competitive advantage. Subsequent theoretical development based on the RBV, such as the Build-Borrow-Buy (BBB) framework (Capron & Mitchell, 2009, 2012), the dynamic capabilities (G. P. Pisano, 2017; Teece & Pisano, 1994), the profiting from innovation (PFI) perspective (G. Pisano, 2006; Teece, 1986), and the absorptive capacity (Cohen & Levinthal, 1990) also provides valuable insights into the problem of external sourcing. When considering the specific case of innovation and the external sourcing of inventions and technical capabilities (Arora, Cohen, & Walsh, 2016), these different theories often give different predictions regarding firms' optimal choice in their technology sourcing strategies. Through the three chapters of my dissertation, I test on different predictions generated by the theories under the context of external technology sourcing in the US manufacturing sectors, and try to draw a more comprehensive picture of when does which theory applies best to a certain technology sourcing situation.

In the first chapter, I look at the relationship between the firms’ position on holding valuable complementary assets (trademarks) with their external technology sourcing strategies. Consistent with the TCE perspective, firms that have valuable complementary assets are more likely to focus on internal innovation rather than externally sourced innovation in its steady state. When firms are entering new industries or new market and facing more dynamic environmental changes, however, their choices conform to the PFI perspective and are more likely to pursue external technology sourcing as they possess valuable complementary assets.

My second chapter is a continuation of the first chapter to study firms’ position on complementary assets when they commercialize external innovation and entering new markets. The focus of this study shifts the attention from the firms’ existing stock of complementary assets to whether they are likely to change their existing complementary assets. Based on PFI, firms are likely to leverage their existing complementary assets when utilizing external innovation. However, I show empirically that under the situation of new market entry, it is more beneficial if the firms can make changes and adjustments to their existing complementary assets, which supports the dynamic capabilities view. This changing existing complementary assets is not in contradict with holding valuable complementary assets in the first chapter. It could be that holding the complementary assets enables the firms to have the capability to efficiently develop new complementary assets to adjust the firms' new position with the new market and external technology.

In the third chapter, I extend to the microfoundation of capabilities (Felin, Foss, Heimeriks, & Madsen, 2012) to look at how the availability of hiring new inventors affects firms' technology sourcing choices. When firms are not able to hire external employees, they are not able to get the new technologies and capabilities associated with those employees. Thus they will substitute with external technology sourcing, especially through acquisition by which they can obtain capabilities and technologies in a bundle. This is consistent with the BBB framework and in contrast to the complementarity prediction by the absorptive capacity argument.

In a nutshell, my dissertation suggests that while valuable resources are key to a firm's success, the capabilities to change and redeploy resources under more disturbance environment may be more important as firms commercialize external technology and innovation. This capability may raise from a firm's experience and existing assets, or may be acquired externally together with external technology sourcing.

# 2. Trademarks, Specialized Complementary Assets, and the External Sourcing of Innovation

In this chapter, I study the relationship between valuable trademarks and a firm's technology sourcing strategy. The Profiting from Innovation (PFI) and Transaction Cost Economics (TCE) perspectives have generated competing predictions regarding firms' historical stock of valuable trademarks and their decision to pursue external technology sourcing. To conduct the empirical analysis, I use a sample of innovator firms in the manufacturing sectors from the Division of Innovative Labor survey, matched to the USPTO trademark data. Consistent with the TCE perspective, I find that a firm's valuable trademarks are negatively correlated with external technology sourcing and are likely to have lower innovation performance. I further show a boundary condition for PFI such that when firms are new entrants to an industry but already holding valuable trademarks, they are more likely to commercialize external technology.

## *2.1 Introduction*

Should firms with high value brands or valuable trademarks focus on developing internal technology innovation themselves or on commercializing external innovation to achieve further growth? This question is becoming important given the recent phenomenon of "brand-driven innovation," where "big companies find growth in new markets by harnessing an unused asset – their brands" (Coumau, Fabius, & Meyer, 2015). For example, the Apple Inc's iPhone product is a revolutionary product that disrupted the mobile phone industry, and it is the result of a collaboration between Apple Inc and AT&T, representing an external innovation effort by Apple. It is a great success as a result of Apple's effort to capitalize their valuable brand to enter new business spaces, and its success also increased its computer business (Sutherland, 2009). However, we do not whether the iPhone success is a coincidence. We still face the puzzle of whether, on average, it would be optimal for firms that have superior brand assets to seek external innovation or to develop their innovations internally? This is an important question for incumbent firms that possess valuable trademark assets and are facing the pressure to grow. While it is also possible for the firms to license out their trademarks as an alternative means to gain profit, it is not within the scope of this study.

The strategic management and technology innovation literature has shown sparse yet contradictory evidence on the relationship between trademark activities and a firm's technology sourcing strategy (Ceccagnoli et al., 2010; Fosfuri, Giarratana, & Luzzi, 2008). This contradiction is also reflected in the different predictions generated by the Transaction Cost Economics (TCE) perspective (Coase, 1937; Williamson, 1975, 1985) and the Profiting from Innovation (PFI) perspective (Teece, 1986, 2006). A firm's valuable trademarks can be considered specialized complementary assets that the firm owns (Ceccagnoli et al., 2010). The TCE perspective suggests that firms holding valuable complementary assets are more likely to pursue R&D internally due to the high potential transaction cost of external innovation and accordingly are likely to have lower performance if they pursue R&D externally. The PFI perspective suggests that firms holding valuable complementary assets can capitalize on their valuable assets and commercialize external innovations to capture the profit generated by external parties, which in turn generates better innovation performance. The two different sets of hypotheses are tested in this study. In addition, most of the empirical studies supporting the PFI view on complementary assets are carried out within an empirical context of technological change or industry emergence (Hill & Rothaermel, 2003; Mitchell, 1989; Moeen & Agarwal, 2017; Rothaermel & Hill, 2005; Tripsas, 1997), and recent theoretical development suggests that external technology sourcing is more likely to happen to incumbent firms with valuable complementary assets during core knowledge discontinuities (Cozzolino & Rothaermel, 2018). Thus, I further test a boundary condition for PFI focusing on firms that are new entrants into an industry but hold valuable trademarks. Note that both incumbents and startups are considered and not distinguished in this study. Even for the new entrants into an industry, they could be either de alio or de novo firms. Only the technology sourcing strategy of whether to develop technology innovation internally or through external sources is considered.

The empirical analysis is based on a sample of US manufacturing firms from the Division of Innovative Labor survey (Arora, Cohen, et al., 2016). I focus on firms that are standalone and that generated a new-to-the-market innovation product during the survey period between 2007 and 2009. I look at the correlation among firms' valuable trademarks, external technology sourcing, and innovation performance. The analysis of firms' existing stock of valuable trademarks and technology sourcing strategies supports the TCE view in that the more valuable the trademarks, the less likely a firm is to pursue external innovation. Additionally, I show that firms with valuable trademark assets and commercializes an external innovation are likely to have lower innovation performance. I also show that firms that own valuable trademarks and are new entrants in an industry are more likely to commercialize an external innovation, which supports the PFI perspective under a boundary condition.

This paper addresses the new phenomenon of brand-driven innovation (Coumau et al., 2015) in the broader context of the division of innovative labor (Arora, Cohen, et al., 2016) and open innovation (West & Bogers, 2014). Building upon existing literature on specialized complementary assets (Ceccagnoli et al., 2010; Fosfuri et al., 2008), this study identifies boundary conditions that firms are more profitable to commercialize external innovation when they possess valuable trademarks. It suggests that firms should reinforce their existing capabilities when focusing on the industries that they already have a competitive advantage, but can better leverage their brand asset and external innovation when they are *de alio* entrants to a new industry.

The remainder of this paper is organized as follows. Section two reviews the literature and generates several hypotheses based on different theoretical perspectives.

In section three, I provide a detailed description of the survey data and the trademark data, document the key variables and methodology, and present descriptive statistics. In section four, I present the regression analysis as well as a series of robustness checks, which provide evidence that is consistent with the hypotheses. Finally, in section five, I present a summary of the findings and a brief discussion.

## *2.2 Literature Review and Theoretical Framework*

### 2.2.1 Complementary assets and technology sourcing

Teece (1986) proposed the Profiting from Innovation (PFI) framework in which he introduced the concept of specialized complementary assets and their importance in the successful commercialization of innovation. Complementary assets are defined very broadly as the resources, capabilities, and assets that are needed to profit from an innovation. They include services such as finance, marketing, and sales, competitive manufacturing, distribution and logistics, and consumer services (Helfat & Lieberman, 2002; Teece, 1986). According to Teece (2006, 1986), specialized complementary assets are so important during the commercialization of an innovation that it is not necessarily the innovator alone who benefits from the innovation but also whoever possesses the necessary complementary assets – including the imitators and technology buyers who did not originally come up with the technology.

Subsequent studies on the relationship between complementary assets and external technology sourcing have two main findings. On the one hand, if firms do not have the necessary complementary assets, they are more likely to be involved in the supply side of external technology sourcing (Gans & Stern, 2003). In the literature on licensing and the market for technology, technology supplier firms without the necessary complementary assets have an incentive to license out the technology to firms that have the complementary assets (Arora & Ceccagnoli, 2006; Gambardella, Giuri, & Luzzi, 2007; Motohashi, 2008). In the literature on alliances, technology supplier firms that do not have the necessary complementary assets have an incentive to find alliance partners that have the complementary assets and commercialize the innovation together (Colombo, Grilli, & Piva, 2006; Fuller & Thursby, 2008; Rothaermel, 2001). On the other hand, and mostly within a context of radical technological change, incumbent firms that possess the necessary specialized complementary assets can capitalize on the entrant's technology through external technology sourcing (Rothaermel & Hill, 2005; Tripsas, 1997) and attain high performance. Moreover, according to Arora and Nandkumar (2012), the existence of a market for technology and the external supply of technology increases the importance of marketing capability (hence, complementary assets) for firm performance. Thus, specialized complementary assets play an important role in the market transaction of technologies and the subsequent commercialization.

This literature has very clear propositions for the choices faced by startups. If critical complementary assets are held by incumbent firms, startups will be technology suppliers rather than commercialize the innovation themselves; if the incumbent's complementary assets are overturned, there is a chance for the startups to commercialize and compete on the product market (Arora & Ceccagnoli, 2006; Gans & Stern, 2003). However, we have relatively less knowledge about the choices of incumbent firms when they hold critical complementary assets. Holding complementary assets enables incumbent firms to have a competitive advantage in conducting innovation (Helfat, 1997; Helfat & Raubitschek, 2000; Tripsas, 1997). In addition to the role in appropriability, complementary assets can also potentially shape the evolutionary paths and enterprise strategy to sustain the incumbent's competitive advantage (Jacobides, Knudsen, & Augier, 2006; Teece, 1986, 2006). Lastly, given the presence of technology suppliers, the incumbent firms can also capitalize on their complementary assets and commercialize the innovation developed externally (Cozzolino & Rothaermel, 2018; Gans & Stern, 2003). Thus, one important task faced by the incumbent firms who holds critical complementary assets is the choice or the balance between internal innovation and external technology sourcing.

In this study, I seek to understand the firm's choice of internal vs. external innovation when they hold a specific type of complementary asset – trademarks. Specifically, as they hold valuable trademarks, do firms choose to commercialize internal or external innovation, and what are the performance implications of their choices? I also take a step further to understand the boundary conditions for their technology sourcing strategy.

### 2.2.2 Trademarks as cospecialized complementary assets

Trademarks are an important complementary asset in which firms invest (Ceccagnoli & Jiang, 2013). Trademarks protect brands, reputation, products, and technologies (Fosfuri & Giarratana, 2009; Fosfuri et al., 2008). Trademark activity is correlated with firms' other marketing efforts, such as advertising (Fosfuri & Giarratana, 2009), number of sales executives (Arora & Nandkumar, 2012), marketing intensity (Melnyk, Giarratana, & Torres, 2014), and is used as a measure of marketing capabilities (Fosfuri et al., 2008). According to Melnyk et al. (2014), the more valuable a trademark is, the more likely the owner firm is to prolong the trademark. They suggest that trademark prolongation is correlated with firm globalization, firm age, marketing intensity, etc.

Trademarks are shown to be correlated with better firm performance (Block, De Vries, Schumann, and Sandner, 2014; Sandner and Block, 2011) and positively correlated with a rival firm's financial market value (Fosfuri & Giarratana, 2009). The literature on innovation also shows a positive correlation between trademark filings and innovation (Allegrezza & Guard Rauchs, 1999; Crass, 2014; Hugo, Ferreira, & Godinho, 2011; Mendonça, Pereira, & Godinho, 2004), and considers trademarks to be an indicator for innovation in certain sectors (Gotsch & Hipp, 2012; Schmoch, 2003; Schmoch & Gauch, 2009). Other studies have also taken a step beyond product innovation and linked trademark activity to specific types of product innovation, such as imitation (Semadeni, 2006; Semadeni and Anderson, 2010) or product differentiation and diversification (Gao & Hitt, 2012).

There is only sparse evidence on the relationship between trademarks and the sourcing of innovation in specific industries, which has generated different conclusions. Fosfuri et al. (2008) study the open source software (OSS) sector and find that firms' involvement with OSS is positively correlated with firms' stock of hardware trademarks but negatively correlated with firms' stock of software trademarks. Ceccagnoli et al. (2010) used trademarks as part of the construction of a measure for cospecialized complementary assets focused on the pharmaceutical industry. Their study suggests that the constructed measure is negatively correlated with external technology sourcing when internal R&D capability is high. They also show that when internal R&D productivity decreases, the demand for external technology increases.

In this study, I view trademarks as a specific type of cospecialized complementary asset to understand the technology sourcing strategy for firms that possess valuable trademarks.

### 2.2.3 Technology sourcing strategies: internal R&D vs. external sourcing

One important question for corporate strategy is a firm's vertical scope and boundary choices (Mahoney, 1992; Novak & Stern, 2008; Teece, 1988, 1996). Boundary choices are not only important for the production process, but also important during innovation. Innovation activities are usually oriented toward problem solving, associated with high uncertainty (Rosenberg, 1996) and complexity (Henderson & Clark, 1990; Rosenberg, 1982). These characteristics are important factors that determine a firm's choice of their innovation boundary. There is a vast literature making the distinction among the division of labor, division of knowledge (Brusoni, Jacobides, & Prencipe, 2009; Brusoni, Prencipe, & Pavitt, 2001; Patel & Pavitt, 1997; Prencipe, 2000), and the division of innovative labor (Arora, Cohen, et al., 2016; Arora & Gambardella, 1994b; Arora & Merges, 2004), suggesting that firms constantly face the choice of internal innovation versus external technology sourcing.

While "make" and "buy" represent the two extremes of a firm's technology strategy, there is a continuum of choices (Rothaermel, 2018), including in-house R&D, market for firms/acquisition (Higgins & Rodriguez, 2006; Mitchell & Shaver, 2003), strategic alliances in the form of equity alliances or joint ventures (Rothaermel, 2001), long-term or short term contracts/licensing, or the arm's length market transactions through the market for technology (Arora, Fosfuri, & Gambardella, 2001). There are also informal means of technology acquisition, such as reverse engineering, hiring or informal interaction (Arora, Cohen, et al., 2016). Because there are so many different choices of technology sourcing strategy, a firm's selection capability, capability gaps, and the internal social frictions are important factors in determining internal vs external sourcing, and which mode of external sourcing to use (Capron & Mitchell, 2009). In this study, I focus on the choice between internal vs. external sourcing, considering only in-house R&D to be internal and all other modes to be external innovation.

In addition to various modes of external technology sourcing, the open innovation literature and several survey studies also emphasize different sources of external technology, including suppliers, customers, other firms/competitors, consultants, commercial labs, engineering service providers, independent inventors, universities or government labs (Arora, Cohen, et al., 2016; Laursen & Salter, 2006, 2014). Firms typically do not restrict their search to a single external source. The number of external sources that firms rely on, defined as external search breadth, is an important measure of openness in assessing a firm's technology sourcing strategy (Laursen & Salter, 2006).

Firms often use concurrent sourcing to both "make" and "buy" simultaneously (e.g., Kapoor, 2013; Luo et al., 2012; Parmigiani, 2007; Parmigiani & Mitchell, 2009). During the innovation process, firms can also combine the internal and external technology and do not have to rely solely on one of them – so-called ambidexterity in technology sourcing (Rothaermel & Alexandre, 2009) or integrative search strategies (Criscuolo, Laursen, Reichstein, & Salter, 2018). Thus, the extent to which firms use both internal and external innovation is another indication of the level of openness for their technology sourcing strategy.

In this study, I use external search breadth and ambidexterity as alternative measures to the binary internal vs. external technology sourcing strategy to understand the relationship between valuable complementary assets and firms' technology sourcing.

### 2.2.4 Trademark and external technology sourcing: different views by TCE and PFI

Although the PFI framework builds on the insights from the Transaction Cost Economics (TCE) perspective, the two theories consider different sets of factors in determining the boundaries of the firm (Teece, 2010). The TCE perspective builds upon the organizational economics theory, and emphasizes the transaction costs that comes with opportunism, principal-agent problem, and incentive issues (Coase, 1937; Williamson, 1975, 1985). Analyses using the TCE framework focus on transactions as the unit of analysis and emphasize the savings on transaction costs in organizational design. The TCE framework implicitly assumes that production costs – which can be thought of as an equivalent for the firm's operational capability – holds constant across organizational types. Thus, the choice between internal and external arrangements is dependent on transaction/governance costs (Teece, 2010). The PFI perspective builds upon the (dynamic) capabilities theory, which theorize about how firms can develop and sustain competitive advantage and earn supernormal profits. The unit of analysis for PFI is the innovating firm and the specific assets that are available to the firm.It focuses on the availability and tradability of assets and capabilities. In essence, the PFI perspective explains the firms' boundary choices to create and capture value through the orchestra of knowledge assets and organizational capabilities, either internally or externally (Teece, 2010).

These differences in TCE and PFI/capabilities perspectives largely complement each other (Foss, 1996; Teece, 1986). However, when considering the specific question of whether firms holding cospecialized assets are more likely to pursue external innovation, the two perspectives can give different predictions.

The TCE perspective suggests that when the marginal cost of internal development is lower than the marginal cost of external sourcing, a firm would prefer the internal source. A key argument for TCE is that transaction costs increase as contractible assets become more specific to the transaction and as complexity increases (Williamson, 1985). The contractual hazards are especially high during the process of external technology sourcing because of the high complexity and the potentially highly specialized assets (Ceccagnoli et al., 2010).

Based on the TCE perspective, the more valuable a firm's historical trademark asset is, the more beneficial it will be if the firm performs internal innovation rather than acquires external innovation. A firm's existing stock of trademarks is filed for its existing products. The firm also has a series of other complementary assets available, such as marketing efforts, brand images, etc. And they usually target a specific consumer base the firm serves. While an internal innovation is likely an extension of a firm's existing product line, it will be more difficult for an external innovation to have a similar impact on consumers without hurting the brand image. According to Decker and Baade (2016), dissimilarity among alliance partners has a negative impact on consumer's brand fit perception and reduces the overall co-branding alliance performance. If a firm can carry out internal innovation to strengthen its existing product line, the firm will prefer to stick to internal innovation. As such, there will be higher complementarity between the new product and the firm's existing marketing efforts and brand images, resulting in higher innovation performance. Thus, on average, the TCE perspective suggests that firms with valuable trademark assets are less likely to source innovation externally.

*H1a. The more valuable a firm's historical trademarks, the less likely it will commercialize externally sourced innovation.*

The PFI perspective, on the other hand, suggests that firms with valuable trademarks may have an incentive to commercialize external innovation. Firms that have a large stock of valuable historical trademarks are likely to have a higher value of specialized complementary assets (Ceccagnoli et al., 2010). With trademark protection, these specialized complementary assets are not assessable by the potential technology suppliers. Based on PFI, if the incumbent firm chooses to commercialize external innovation, they can access the external technical capability and capitalize on their valuable trademarks through the marketing process and their consumers.

*H1b. The more valuable a firm's historical trademarks, the more likely it will commercialize externally sourced innovation.*

### 2.2.5 Performance implications for firms that have valuable trademarks and pursue external technology sourcing

The different predictions by the TCE and PFI perspectives on a firm's technology sourcing strategies when it owns valuable trademarks can also be reflected by the innovation outcome as it commercializes external technology. Based on the TCE perspective (Coase, 1937; Williamson, 1975, 1985), it is not favorable for firms that have valuable trademarks to pursue external innovation compared to internal innovation. This is because external innovation potentially incurs higher transaction costs to the firm. As a result, the firms with valuable trademarks and commercialized external innovation are likely to have lower performance, compared to those that commercialize internal innovation. Based on the PFI perspective (Teece, 1986, 2006), firms that have valuable trademarks can commercialize external innovation to capture the value created by external parties. This can be in addition to what the firms are already capturing from their internal innovation. Thus, the firms can potentially have higher innovation performance as they own valuable trademarks and pursue external technology sourcing. Based on the performance implications, there are two additional hypotheses for the technology sourcing strategy by firms with valuable trademarks.

*H2a. (TCE) Firms that have valuable trademarks and commercialize external innovation are likely to have worse innovation performance.*

*H2b. (PFI) Firms that have valuable trademarks and commercialize external innovation are likely to have better innovation performance.*

### 2.2.6 Boundary conditions for PFI: when firms benefit from valuable trademarks and external technology sourcing

In contrast to the Schumpeterian gales of creative destruction (Schumpeter, 1942), the PFI perspective was proposed to explain the phenomenon, in which the value created by an innovation is not always captured by highly creative firms (Teece, 2010). Both theories, as well as the vast empirical evidence that emphasizes the importance of complementary assets (Hill & Rothaermel, 2003; Mitchell, 1989; Moeen & Agarwal, 2017; Rothaermel & Hill, 2005; Tripsas, 1997), are often explained within a context of discontinuity: technological changes, sub-industry emergence, etc. Although these industry-level shifts provide an experimental setting to study the role of complementary assets, the implication on the technology sourcing decisions for an average incumbent firm with complementary assets can be limited. Most of the time, firms are too deep into an industry to be aware of the gradual shifts, or are constantly facing the choice of whether to continue their existing path or to try a new direction.

Cozzolino and Rothaermel (2018, Figure 1) provide a comprehensive discussion of different cooperation/competition strategies under different competitive landscapes, making a distinction between knowledge discontinuity and complementary assets discontinuity. Based on their discussion, when the incumbent's complementary assets are valuable, the incumbent firms are likely to pursue external sourcing and capitalize on their complementary assets if their existing knowledge is not needed in the new market/technology; they are likely to keep steady state competition when their existing knowledge is still valuable. Based on their discussion, when a firm has valuable trademarks, it is more likely to commercialize an external innovation if it is relatively new in a certain industry – especially when it does not have the necessary technical capabilities. This does not mean the company itself is a startup; rather, it could be an existing firm entering a new sub-industry. With that, I further test a boundary condition: firms that are new to an industry, but have valuable trademarks, are more likely to commercialize an external innovation, and have better performance.

*H3a. If a firm is new to an industry, the more valuable trademarks it has, the (even) more likely it will commercialize an external innovation.*

*H3b. If a firm is new to an industry, having valuable trademarks and commercializing external innovation will result in better innovation performance.*

## 2.3 Data and Methods

### 2.3.1 The United States (US) Trademark System: A Brief Introduction

A trademark is a combination of words, phrases, symbols, or designs that identifies and distinguishes the goods and services of one party from those of others. A trademark functions as a source identifier and conveys information on the origin of goods and services to consumers. Trademarks help consumers distinguish among competing producers, thereby reducing search costs (Graham, Hancock, Marco, & Myers, 2013).

The owner of a trademark can prevent others from using the same or a similar label for their goods and services, if such use might confuse consumers. In the United States (US), trademark rights are established using the mark on or in connection with goods and services, which do not require formal state or federal registration (common law rights). However, there are additional benefits to formal registration compared to common law rights. For example, federal registration enables nationwide protection of the trademark and provides a formal searchable notice to potential infringers. It also clarifies the property rights of the trademarking firm and prevents additional lawsuits. [1] A trademark can be renewed and maintained as long as the owner pays the prescribed fees, files the required documents and keeps the product or services in commerce (Graham et al., 2013; Melnyk et al., 2014). Terminating a particular trademark may result in serious financial loss because the original firm's competitors can adopt the abandoned trademark and benefit from it (Melnyk et al., 2014).

In this study, I match the USPTO trademark data with the survey respondents to collect information on their trademark filings.

---

[1] https://sausserspurrlaw.wordpress.com/2013/07/02/what-is-a-common-law-trademark-2/

### 2.3.2 Sample

The Division of Innovative Labor (DOIL) survey data generated in 2010 provide information about firms' new product development activities at the business unit level during the period 2007 to 2009. The sampling frame was the Dun and Bradstreet (D&B) selectory database, which provides the most complete publicly available frame for the United States. The sampling process is stratified along multiple dimensions, including firm size and industry. For a detailed description of the sampling process, survey procedures, response rates across industries, and other information regarding the data, refer to Arora et al. (2016). Unless otherwise indicated, this study uses survey sample weights across the regression analyses. The sample weight was constructed using the Census data on the population of firms by industry, size strata and age to correct for non–response bias (Arora, Cohen, et al., 2016).

The DOIL survey employs a representative sample of the population of firms in the U.S. manufacturing sector, with 5,175 respondents at the business unit level. Unlike several other innovation surveys (e.g., Cohen et al., 2000; Levin et al., 1987), the DOIL survey is not restricted to R&D performers. It includes innovators, imitators, and firms that do not innovate by asking whether the firms had introduced a new product that is new to the market or new to the firm and requests further information about their key innovations (Arora, Cohen, et al., 2016). The survey also provides information on whether the innovator firms acquired their key innovation externally and on the sources and channels from which the firms obtained the external innovation. This particular feature of the survey enables the comparison of trademark activities across different types of firms and innovators. In particular, the availability of the sources of innovation makes it possible to compare firms' trademark activity between internally and externally sourced innovation, which is the focus of this study.

For further detail at the industry level, I match the DOIL survey with the National Establishment Time-Series (NETS, 2013 version) manufacturing database. The NETS database collects archival establishment data from D&B into a time-series database of establishment information. It records detailed information for industry classifications (up to eight-digit SIC and six-digit NAICS) for each establishment. Estimated annual sales are also provided at the establishment level: for standalone establishments, the sales are reported at the firm level; for other establishments, industry sales per employee are used to estimate the establishment sales. To accurately assign the six-digit NAICS industry classification to the survey respondents, I combine information from the NETS manufacturing database and the establishment's self–report of its main line of business. Following Bei's (2018) definition of the NETS firm structure in 2010, I collect information on the respondents' parent firm's year of establishment and diversification as controls in this study.

The sample of this study is a subsample of the original survey as defined by the following criteria. First, I focus on innovator firms that generated new-to-the-market innovations (based on the survey questions) to study the relationship between the source of their innovation (internal vs. external) and their trademark activity. The other types of firms, including firms that did not commercialize a new-to-the-market innovation and firms with no innovations, are not included in the main analysis. Following Arora et al. (2016), to obtain the sample of innovator firms, I exclude any innovator firm that "reported either that they introduced their most significant innovation outside of the 2007–2009 time window, or reported zero 2009 sales revenue due to this innovation". Second, I focus on standalone firms and leave out subsidiaries that have a parent firm in the main analysis. This is because trademarks are usually filed at the firm level rather than at the establishment level. Thus, a subsidiary's trademark activity may be confounded by its parent company's trademark activity, introducing measurement error into the analysis. Full sample analysis, including non-standalone firms, is also available in the robustness tests. Last, the sample is reduced due to data availability caused by imperfect matching with NETS as a result of (potential) M&A and name changes. Excluding missing values in the control variables, the final sample consists of 573 innovator-standalone firms. The actual number of observations for each analysis is further subject to the availability of responses for other survey-based variables.

The survey is linked to the United States Patent and Trademark Office (USPTO) trademark data (Graham *et al.*, 2013) to obtain the innovator's trademark information. I link the survey respondents with trademark filing information by firm name and further refine the matching by checking the trademark classification and the respondents' reported industry classification and product line (Arora, Bei, & Cohen, 2016). The survey is also linked to the PATSTAT database to obtain information on patent filings through a similar procedure.

## 2.3.3 Variables

### 2.3.3.1 Dependent variables

*Measurements for external technology sourcing*

Three different measures are constructed to assess the level of openness in the respondent firms' technology sourcing strategy: whether an external technology source is involved, technology search breadth (Laursen & Salter, 2006), and the level of ambidexterity of technology search (Rothaermel & Alexandre, 2009).

*Indicator of external sourcing*: The survey also asks respondents about the source of their innovation, enabling them to provide multiple choices for a list of sources. Following Arora et al. (2016, Table 3), I identify innovation as external if the respondent indicates any of the external sources, including a supplier, a customer, other firms in the industry, a consulting service provider, an independent inventor, or a university. If a respondent does not indicate any of the external sources, then the innovation is considered internal. A binary indicator variable is generated to indicate whether the respondents commercialize an external innovation (=1).

*Technology sourcing breadth*: The measure of technology search breadth follows Laursen and Salter (2006). Because multiple sources are indicated in the survey, I add up the number of sources mentioned by each respondent to construct the measure of technology search breadth. Due to the differences in survey design, the maximum number of sources in the DOIL survey is 6, which is less than Laursen and Salter's original analysis (16 sources). The DOIL survey also does not have information on the quantitative measure of the importance of each of the sources. Thus, while the information drawn from the breadth measure is limited, it still provides useful insights into understanding firms' technology sourcing strategy.

*Integration*: The measure of integration follows the ambidexterity measure by Rothaermel and Alexandre (2009) and the integration measure by Criscuolo et al. (2018). In the survey, it is possible that the respondents indicate that internal innovation is also a source of the focal innovation, or if the innovation largely originates from the R&D activity by the respondents. Combining the information for both the internal and external sources, an indicator variable is generated that equals zero if the innovation is purely based on internal innovation, equals one if the innovation involves both internal and external sources, and equals two if the innovation solely relies on external sources. This is also different from the original measure in the other two studies because their measures have more details regarding the knowledge sourcing strategies based on the survey information. But again, this measure provides useful insights in understanding firms' technology sourcing strategy.

*Measurements for innovation performance*

*Market share increase*: In the survey, respondents were asked about the change in their market share over the sample period. Their response could be either a percentage number or an indication of whether their market share increased or decreased. Following Arora et al. (2016), I use a dummy variable indicator of market share increase as a measure of a firm's overall innovation performance. Additional analyses are performed for the subsample of respondents that provided the numeric percentage changes as robustness checks.

*Percentage of total sales*: The survey respondents are asked to indicate what was the percent of total sales in 2009 that comes from their focal innovation. This information is used as an alternative measure of innovation performance.

*Ratio of innovation sales*: The survey respondents are also asked to indicate the percentage of total sales in 2009 that comes from their all innovation activities. Combining this with the previously mentioned question on focal innovation sales, another measure of innovation performance is generated to be the ratio of the sales of their focal innovation over the sales of their total innovation. This provides an indication of how important this focal innovation is among the firm's entire set of innovative activities.

All performance measures are log transformed (except for binary variables) to approximate normal distributions.

#### 2.3.3.2 Independent variables

*Firms with valuable historical trademarks*

I use two different measures to proxy for valuable historical trademarks. First, based on the matched trademark filings, I count the total number of trademarks that were filed before 2006 and that were still alive by 2006. Approximately 46% of the respondents of the original survey sample had at least one active trademark before 2006. Among those with active existing trademarks, I choose the median number of old but alive trademarks as the cutoff value to categorize firms as having valuable historical trademarks. Table 1 shows that 21% of the final sample of innovator-standalone firms are categorized as having valuable trademarks.

Second, as an alternative measure of valuable trademarks, I collect the top 500 valuable brands in 2010 from Brandirectory.com and match them to the DOIL respondents' companies. The matching is at the firm level, and any respondents with a match among the 500 top brands are considered as having valuable trademark assets. Because of the low number of top brands on the list, only approximately 1% of the sample is considered as having top brands (Table 2). Firms with top brands are relatively sparse and only focus on a few industries (see Table A1 for a breakdown by industry), but they can provide some insights into the value of trademark assets as an alternative measure.

*New entrant of an industry*:

To identify firms that have newly entered the industry, I utilize one of the survey questions asking "whether the firm had entered the specified industry for less than five years" to create an indicator variable. In contrast with the interpretation of Arora et al. (2016), I do not consider firms having less than five years of experience to be startups because the actual starting year of the establishment or the headquarters firm can be long before the five-year threshold. If the starting year of a firm is also within five years, the respondent is likely to be a startup. If the starting year of a firm is long before the five-year threshold, it is possible to be an incumbent firm diversifying into another related industry or engaging in corporate entrepreneurship. The data on actual start year of the (headquarter) firm are obtained from the NETS database and used as a control in the empirical analysis.

**2.3.3.3 Control variables**

*New trademark filings during the survey period:* The matched trademark filings from USPTO are divided into two parts: one is the new trademark filings during the survey period from 2006 to 2010; the other is firms' old trademark filings before 2006 that were still active by the year 2006. For new trademark filings, I generate an indicator variable equal to one if the respondents had at least one trademark filed during the survey period, and zero otherwise.

*Product patent:* Patenting information is based on the survey question asking whether the company patents any part of the innovation.

*Business unit (BU) size:* In the survey, business units are defined by a firm's activities within a given NAICS industry. The survey provides the number of employees in the focal industry of the respondent.

*Firm size:* the total number of employees at all sites, obtained through Dun & Bradstreet.

*Industry-fixed effect:* The industry-fixed effect is reported based on the three-digit NAICS code for 21 industries (Table A1).

*Firm patenting*: Firm's patenting information is obtained by linking the respondents with the PATSTAT patent database. A count variable is generated by including all patents filed after 2000, and log-transformed to approximate a normal distribution.

*Single sector firms, and vertical integration*: Following Rothaermel and Alexandre (2009), I also control for firm structure in terms of diversification and vertical integration. Diversification is obtained from the NETS database as the number of sectors in which the headquarters firm operates. Vertical integration is obtained from the survey question asking whether a main customer or important supplier is part of the same firm.

*Firm start year*: Firm age is controlled using the firm start year, obtained from the NETS database and based on the Bei (2018) definition of the 2010 firms.

#### 2.3.3.4 Empirical method

I use the linear probability model to analyze the relationship between valuable trademarks and external technology sourcing. For the technology search breadth and integration as dependent variables, I use ordered logit following Laursen and Salter (2004). For the analysis on innovation performance, the linear probability model is used on binary dependent variables (market share increase), and ordinary least square is used on other measures. I use the *svy* setting in STATA to ensure that the estimated standard error is robust and the sample weight is applied properly for the results to be generalizable to the entire population. The regressions are performed at the respondent level, and all controls, including industry-fixed effect, are applied throughout the analysis.

#### 2.3.3.5 Descriptive statistics

Table 1 shows a breakdown of trademark activities by different categories. On average, 39% of DOIL firms filed for new trademarks during the sample period, and 46% of them have existing trademarks. Approximately one-fourth of the firms are considered as having valuable trademark assets, and approximately one-sixth of them are among the top 500 most valuable brands. This number is especially high for non-standalone firms, possibly due to trademark activity by their parent firms. Because of this confounding factor, the main analysis of this study focuses on standalone firms. A more detailed breakdown of trademark activities by different industries is also available in Appendix I.

**Table 1: Trademark activities by category**

| Subsample | Category | Freq | %NewTM | %Old TM | %Tmasset | %Topbrand |
|---|---|---|---|---|---|---|
| All | All | 4201 | 0.35 | 0.42 | 0.21 | 0.13 |
| | Standalone | 3167 | 0.21 | 0.28 | 0.08 | 0.01 |
| | Non-standalone | 1034 | 0.78 | 0.87 | 0.60 | 0.02 |
| Standalone | New-to-the-market | 573 | 0.43 | 0.50 | 0.20 | 0.01 |
| | New-to-the-firm | 758 | 0.22 | 0.26 | 0.08 | 0.01 |
| | No innovation | 1762 | 0.14 | 0.21 | 0.04 | 0.01 |
| Innovator & standalone | Internal innovation | 301 | 0.41 | 0.52 | 0.22 | 0.02 |
| | External innovation | 272 | 0.45 | 0.47 | 0.18 | 0.01 |

Note: Sample weights not applied

Among the different types of innovators, innovators who generate new-to-the-market products have a higher propensity to trademark compared to imitators who generate new-to-the-firm products or other firms that do not innovate. This difference is consistent across different trademark-based measures. This study focuses exclusively on firms that commercialize new-to-the-market products.

The descriptive statistics of the key variables and the correlation matrix for the final sample are shown in Table 2 and 3. This study focuses on 573 standalone-innovator firms in the survey sample.

**Table 2: Descriptive statistics (Standalones only)**

| | Variable | Obs | Mean | Std. Dev. | Min | Max | Source |
|---|---|---|---|---|---|---|---|
| 1 | New Trademarks | 573 | 0.43 | 0.50 | 0.00 | 1.00 | USPTO |
| 2 | External | 573 | 0.47 | 0.50 | 0.00 | 1.00 | DOIL |
| 3 | Breath | 563 | 0.70 | 0.93 | 0.00 | 6.00 | DOIL |
| 4 | Integrate | 573 | 0.74 | 0.85 | 0.00 | 2.00 | DOIL |
| 5 | Topbrand | 573 | 0.02 | 0.12 | 0.00 | 1.00 | Brandirectory.com |
| 6 | TMasset | 573 | 0.20 | 0.40 | 0.00 | 1.00 | USPTO |
| 7 | New Entry | 573 | 0.07 | 0.26 | 0.00 | 1.00 | DOIL |
| 8 | Uni Sector | 573 | 0.70 | 0.46 | 0.00 | 1.00 | NETS |
| 9 | Vertical Integration | 573 | 0.27 | 0.44 | 0.00 | 1.00 | DOIL |
| 10 | Firm Patenting (log) | 573 | 0.57 | 1.29 | 0.00 | 9.13 | PATSTAT |
| 11 | Product Patent | 573 | 0.48 | 0.50 | 0.00 | 1.00 | DOIL |
| 12 | Market Share Increase (0/1) | 526 | 0.64 | 0.48 | 0.00 | 1.00 | DOIL |
| 13 | Market share change (%, log) | 458 | 1.16 | 2.69 | -4.25 | 6.21 | DOIL |
| 14 | % Total Sales (log) | 536 | 2.42 | 1.09 | 1.10 | 4.32 | DOIL |
| 15 | % Inno Sales (log) | 523 | -0.44 | 0.88 | -2.99 | 3.22 | DOIL |
| 16 | BU Size | 573 | 1.93 | 0.85 | 0.48 | 5.48 | DOIL |
| 17 | Firm Size | 573 | 1.85 | 0.82 | 1.00 | 5.51 | D&B |
| 18 | Firm Start Year | 573 | 1976.21 | 29.40 | 1842 | 2009 | NETS |

**Table 3: Correlation matrix**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | | | | | | | | | | | | | | | | | |
| 2 | 0.04 | 1.00 | | | | | | | | | | | | | | | | |
| 3 | 0.03 | 0.80 | 1.00 | | | | | | | | | | | | | | | |
| 4 | 0.00 | 0.91 | 0.68 | 1.00 | | | | | | | | | | | | | | |
| 5 | 0.05 | -0.02 | -0.04 | -0.02 | 1.00 | | | | | | | | | | | | | |
| 6 | 0.48 | -0.03 | -0.01 | -0.04 | 0.07 | 1.00 | | | | | | | | | | | | |
| 7 | 0.06 | 0.01 | 0.02 | 0.00 | -0.03 | -0.05 | 1.00 | | | | | | | | | | | |
| 8 | -0.22 | 0.06 | 0.07 | 0.08 | -0.07 | -0.41 | 0.05 | 1.00 | | | | | | | | | | |
| 9 | 0.09 | 0.08 | 0.12 | 0.08 | 0.13 | 0.12 | -0.01 | -0.06 | 1.00 | | | | | | | | | |
| 10 | 0.37 | 0.03 | 0.05 | 0.03 | 0.08 | 0.49 | -0.06 | -0.24 | 0.08 | 1.00 | | | | | | | | |
| 11 | 0.31 | -0.02 | 0.03 | -0.03 | -0.02 | 0.17 | 0.10 | -0.05 | 0.07 | 0.38 | 1.00 | | | | | | | |
| 12 | 0.00 | 0.06 | 0.10 | 0.04 | -0.06 | -0.04 | 0.10 | 0.04 | -0.06 | 0.03 | 0.05 | 1.00 | | | | | | |
| 13 | 0.02 | 0.05 | 0.10 | 0.01 | -0.03 | -0.07 | 0.17 | 0.06 | -0.07 | 0.07 | 0.12 | 0.90 | 1.00 | | | | | |
| 14 | -0.13 | 0.00 | 0.03 | 0.02 | -0.03 | -0.15 | 0.18 | 0.17 | -0.05 | 0.01 | 0.06 | 0.18 | 0.27 | 1.00 | | | | |
| 15 | -0.06 | -0.02 | -0.06 | -0.01 | 0.00 | -0.01 | 0.01 | 0.04 | -0.05 | -0.08 | -0.06 | 0.05 | 0.04 | 0.53 | 1.00 | | | |
| 16 | 0.36 | 0.00 | 0.01 | -0.02 | 0.24 | 0.52 | -0.10 | -0.46 | 0.26 | 0.46 | 0.26 | -0.04 | -0.04 | -0.28 | -0.20 | 1.00 | | |
| 17 | 0.39 | 0.02 | 0.02 | 0.01 | 0.11 | 0.60 | -0.12 | -0.55 | 0.18 | 0.54 | 0.21 | -0.09 | -0.11 | -0.23 | -0.13 | 0.84 | 1.00 | |
| 18 | -0.12 | -0.02 | 0.02 | 0.00 | -0.10 | -0.34 | 0.19 | 0.38 | -0.09 | -0.12 | 0.04 | 0.15 | 0.19 | 0.23 | 0.04 | -0.36 | -0.47 | 1.00 |

## *2.4 Results*

### 2.4.1 Firms that have valuable trademarks are less likely to use external innovation

In the first analysis, I ask whether the historical stock of valuable trademark assets is correlated with firms' technology sourcing strategy. Theoretical analysis based on PFI and TCE generates a set of competing hypotheses. Drawing on the PFI perspective (Teece, 1986, 2006) and subsequent research on complementary assets and technology sourcing (e.g. Arora and Ceccagnoli, 2006; Gambardella et al., 2007; Motohashi, 2008), a firm's valuable historical trademarks may give the firm a competitive advantage in pursuing external technology sourcing. From the TCE perspective (Coase, 1937; Williamson, 1975, 1985), however, firms are better off developing innovation internally if they own valuable cospecialized complementary assets. Thus, they are less likely to use external innovation, and if they do, it usually means lower overall performance.

In Table 4, I look at the correlation between valuable trademarks and external technology sourcing strategy. Two different measures of valuable historical trademarks are used, categorized by either the top-valued brand (Columns 2, 4, 6) or the number of old trademarks that are still active (Columns 3, 5, 7). And three different measures of external technology sourcing strategy are used: whether firms use any external technology (Columns 1, 2, 3), the external search breadth (Columns 4, 5) and whether it integrates both internal and external innovation (Columns 6, 7). Column 1 includes only the control variables.

**Table 4: Firms with valuable trademarks are less likely to commercialize external innovation**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | | External | | Breath | | Integrate | |
| | OLS | OLS | OLS | Ologit | Ologit | Ologit | Ologit |
| Top Brand (H1a) | | -0.47*** | | -3.21*** | | -1.84*** | |
| | | (0.14) | | (1.59) | | (0.85) | |
| TM Asset (H1a) | | | -0.23*** | | -0.85*** | | -0.90*** |
| | | | (0.08) | | (0.40) | | (0.36) |
| New Trademarks | 0.14*** | 0.14*** | 0.18*** | 0.44*** | 0.58*** | 0.43** | 0.58*** |
| | (0.05) | (0.05) | (0.06) | (0.22) | (0.22) | (0.23) | (0.23) |
| New Entry | -0.17** | -0.17** | -0.17** | -0.69** | -0.68** | -0.77** | -0.77** |
| | (0.08) | (0.09) | (0.09) | (0.40) | (0.41) | (0.44) | (0.45) |
| Uni Sector | 0.15*** | 0.15*** | 0.14** | 0.48+ | 0.43 | 0.58** | 0.57** |
| | (0.07) | (0.07) | (0.07) | (0.37) | (0.37) | (0.30) | (0.30) |
| Vertical Integration | 0.13*** | 0.13*** | 0.13*** | 0.68*** | 0.67*** | 0.50** | 0.52*** |
| | (0.06) | (0.06) | (0.06) | (0.27) | (0.26) | (0.27) | (0.26) |
| Firm Patenting | -0.02 | -0.02 | 0.00 | -0.03 | 0.03 | -0.10 | -0.01 |
| | (0.03) | (0.03) | (0.03) | (0.14) | (0.14) | (0.13) | (0.14) |
| Product Patent | -0.08+ | -0.08* | -0.08* | -0.17 | -0.16 | -0.25 | -0.26 |
| | (0.06) | (0.06) | (0.05) | (0.23) | (0.23) | (0.24) | (0.24) |
| BU Size | -0.02 | -0.00 | -0.02 | 0.23 | 0.11 | -0.09 | -0.14 |
| | (0.06) | (0.06) | (0.06) | (0.32) | (0.32) | (0.30) | (0.28) |
| Firm Size | -0.00 | -0.02 | 0.02 | -0.33 | -0.11 | -0.08 | 0.08 |
| | (0.07) | (0.07) | (0.07) | (0.39) | (0.39) | (0.34) | (0.34) |
| Firm Start Year | -0.00+ | -0.00+ | -0.00* | -0.00 | -0.00 | -0.01 | -0.01+ |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | 3.26* | 3.44* | 3.60* | | | | |
| | (2.27) | (2.27) | (2.29) | | | | |
| Observations | 573 | 573 | 573 | 563 | 563 | 573 | 573 |
| R-squared | 0.08 | 0.09 | 0.10 | | | | |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

On average, a firm is 47% less likely to pursue external innovation if it is among the top 500 valuable brands (Column 2) and is 23% less likely to do so if it is among the firms with valuable existing trademarks (Column 3). The correlations between both trademark measures are negative and significantly different from zero when looking at other measures of technology strategy using the ordered logit model, suggesting that the more valuable trademarks firms own, the less open they are when crafting their technology sourcing strategy: less likely to use multiple external sources of innovation (Columns 4, 5) and are less likely to rely solely on external innovation (Columns 6, 7). I also show the marginal effects for each of the different outcomes in Figure 1.

These different measures of valuable trademarks and external sourcing strategies show strong evidence to support the TCE perspective in Hypothesis 1a, that is, the more valuable a firm's historical trademarks, the less likely they will commercialize externally sourced innovation. The PFI perspective in Hypothesis 1b is rejected.

### 2.4.2 Innovation performance for firms with valuable trademarks and commercialize external innovation

From the previous discussion, the PFI and TCE perspectives also give different predictions regarding firms' innovation performance as they own valuable historical trademarks and pursue external technology sourcing. I test this relationship using several measures of innovation performance constructed from the survey, shown in Table 5. Because the top 500 brand measure represents only a very small portion of the sample and represents a few of the industries (see Table 1 and Appendix I), I only use the number of old trademarks as the indicator of valuable trademarks from here.

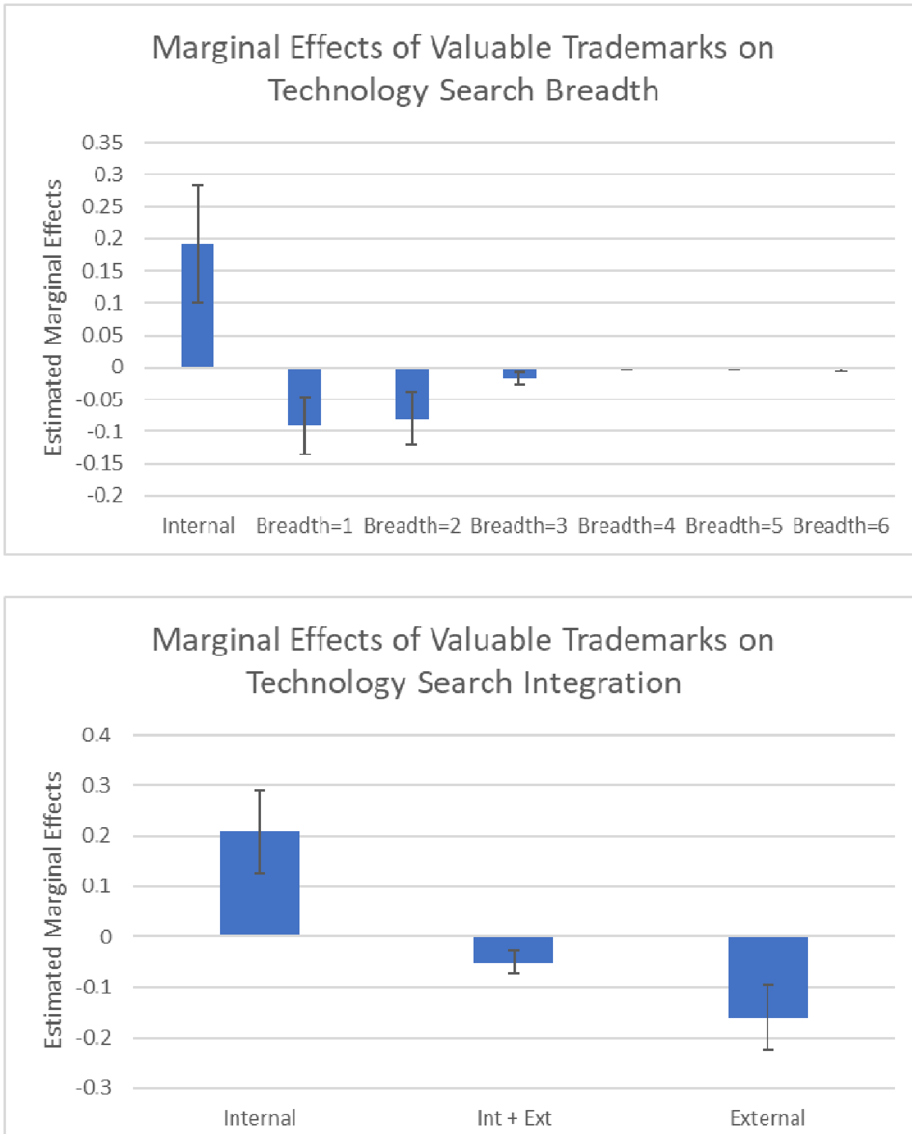


**Figure 1: Marginal effects graphs for Ordered Logit analysis**

In Table 5 Column 1, I include all of the control variables and the indicator for external innovation, valuable trademarks without the interaction term. On average, external innovation is positively correlated with an increase in market share, while firms that have valuable trademarks do not significantly have an increase in market share. In Column 2, I add the interaction term of external innovation and valuable trademarks and show a significantly negative correlation with the dependent variable. The result suggests that firms with valuable trademarks and that pursue external technology sourcing are 32% less likely to have an increase in their market share. In Columns 3 and 4, I use technology search breadth and integrating internal and external technologies instead of a binary indicator of external sourcing and show the interaction term with valuable trademarks. Consistent with the baseline analysis (Column 2), technology search breadth combined with valuable trademarks is also negatively correlated with innovation performance. In Column 4, both types of external innovation (with or without internal innovation) show a negative correlation when interacting with valuable trademarks, and the difference between the two is not significant.

In Columns 5, 6, and 7, I use alternative measures of innovation performance to test the interaction term between external sourcing and valuable trademarks. Using the absolute percentage change in market share (Column 5), the focal innovation product's sales as the percentage of total sales (Column 6), the focal innovation product's sales as the ratio of total innovation sales (Column 7) all consistently show a negative correlation between the interactive terms with innovation performance.

**Table 5: Innovation performance of firms have valuable trademarks and use external technology**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | | | % Total | % Inno |
| VARIABLES | | Increase in MS (0/1) | | | ΔMS | Sales | Sales |
| | | | Breadth | Ext only | | | |
| External | 0.10** | 0.13*** | 0.09*** | 0.10* | 0.82*** | 0.03 | 0.05 |
| | (0.05) | (0.05) | (0.03) | (0.06) | (0.32) | (0.11) | (0.09) |
| External*TMasset | | -0.32*** | -0.20*** | -0.36** | -2.00*** | -0.77*** | -0.88** |
| (H2a) | | (0.15) | (0.08) | (0.18) | (0.88) | (0.34) | (0.31) |
| TMasset | -0.06 | 0.06 | 0.03 | 0.06 | 0.04 | 0.30 | 0.64** |
| | (0.10) | (0.12) | (0.11) | (0.12) | (0.74) | (0.29) | (0.21) |
| Ext+Int | | | | 0.17*** | | | |
| | | | | (0.07) | | | |
| Ext+Int*TMasset | | | | -0.31* | | | |
| (H2a) | | | | (0.19) | | | |
| Firm Patenting | 0.07*** | 0.08*** | 0.08*** | 0.08*** | 0.54*** | 0.16*** | 0.06 |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.14) | (0.08) | (0.07) |
| New Trademarks | -0.06 | -0.06 | -0.04 | -0.06 | -0.36 | -0.23** | 0.02 |
| | (0.06) | (0.06) | (0.06) | (0.06) | (0.35) | (0.13) | (0.09) |
| New Entry | 0.12 | 0.15+ | 0.21*** | 0.15+ | 1.45*** | 0.66*** | 0.03 |
| | (0.11) | (0.11) | (0.10) | (0.11) | (0.64) | (0.27) | (0.24) |
| Uni Sector | -0.01 | -0.01 | 0.00 | -0.01 | -0.18 | 0.17 | 0.03 |
| | (0.07) | (0.07) | (0.07) | (0.07) | (0.42) | (0.14) | (0.12) |
| Vertical Integration | -0.14*** | -0.14*** | -0.14*** | -0.14*** | -0.63** | 0.09 | 0.04 |
| | (0.06) | (0.06) | (0.06) | (0.06) | (0.37) | (0.14) | (0.09) |
| Product Patent | 0.07+ | 0.07+ | 0.05 | 0.07+ | 0.67*** | 0.11 | -0.06 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.32) | (0.12) | (0.09) |
| BU Size | 0.09* | 0.09* | 0.11*** | 0.09* | 0.66*** | -0.29*** | -0.27*** |
| | (0.06) | (0.06) | (0.06) | (0.06) | (0.30) | (0.13) | (0.10) |
| Firm Size | -0.07 | -0.08 | -0.09+ | -0.08 | -0.88*** | -0.10 | -0.03 |
| | (0.07) | (0.07) | (0.07) | (0.07) | (0.39) | (0.16) | (0.13) |
| Firm Start Year | 0.00*** | 0.00** | 0.00** | 0.00** | 0.01*** | 0.00 | -0.00* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | -3.47** | -3.00* | -2.74+ | -3.09* | -24.18*** | 2.66 | 4.99* |
| | (2.03) | (2.05) | (2.00) | (2.08) | (11.74) | (4.72) | (3.36) |
| | | | | | | | |
| Observations | 526 | 526 | 518 | 526 | 458 | 536 | 523 |
| R-squared | 0.14 | 0.15 | 0.16 | 0.15 | 0.21 | 0.13 | 0.11 |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

The analysis of innovation performance also supports the TCE perspective (Hypothesis 2a) but rejects the PFI perspective (Hypothesis 2b). All of the empirical analyses so far suggest that firms that have valuable trademarks and commercialize external innovation are more likely to have worse innovation performance.

### 2.4.3 Technology sourcing strategy for new entrants with valuable trademarks

In the last analysis, I further test under what condition the PFI hypothesis holds. Firms with valuable trademarks tend to focus on internal innovation due to the potential high transaction cost of external innovation. However, when internal development is too hard, as in the case of core knowledge discontinuity (Cozzolino & Rothaermel, 2018), technological changes and industry emergence (Hill & Rothaermel, 2003; Mitchell, 1989; Moeen & Agarwal, 2017; Rothaermel & Hill, 2005; Tripsas, 1997), they may be able to capitalize on their valuable complementary assets, and that is when they will choose to commercialize external innovation. Specifically, I test when a firm is a new entrant in the industry. If the firm has valuable trademarks, it is likely that the firm is an incumbent firm and diversifying into a new (sub-)industry, rather than a startup. Under this situation, the firm is more likely to use external innovation.

In Table 6, I show the technology sourcing strategy and innovation performance for new entrant firms. Columns 1, 2, and 3 test whether firms are more likely to pursue an external sourcing strategy. The results show clearly that new entrants are less likely to commercialize external innovation if they do not have valuable trademarks, but are much more likely to commercialize external innovation if they have valuable trademarks. Columns 4, 5, and 6 test the innovation performance of new entrants. While the coefficient on external innovation with valuable trademarks is negative and significant, the coefficient on the three-way interaction term does not differ significantly from zero. This suggests that new entrants with valuable trademarks may not have better performance as they pursue external technology sourcing – but also not worse.

With this last analysis, Hypothesis 3a is supported. If a firm is new to an industry, the more valuable trademarks it has, the more likely it will be to commercialize an external innovation. This is consistent with the PFI perspective and is thus identified as a boundary condition for PFI to hold.

**Table 6: Technology sourcing strategy and performance for firms as new entrants**

| VARIABLES | (1) External | (2) Breath | (3) Integration | (4) ΔMS | (5) % Total Sales | (6) % Inno Sales |
|---|---|---|---|---|---|---|
| | OLS | Ologit | Ologit | OLS | OLS | OLS |
| External | | | | 0.12*** | -0.01 | 0.02 |
| | | | | (0.06) | (0.12) | (0.09) |
| TMasset | -0.27*** | -1.00*** | -1.06*** | 0.05 | 0.26 | 0.62*** |
| | (0.08) | (0.40) | (0.35) | (0.12) | (0.29) | (0.21) |
| External*TMasset | | | | -0.32*** | -0.83*** | -0.92*** |
| | | | | (0.16) | (0.33) | (0.33) |
| New Entry | -0.22*** | -0.92*** | -1.02*** | 0.08 | 0.33 | -0.16 |
| | (0.08) | (0.42) | (0.45) | (0.15) | (0.33) | (0.35) |
| External*New Entry | | | | 0.20 | 0.83** | 0.48 |
| | | | | (0.16) | (0.44) | (0.38) |
| TMasset*New Entry | 1.00*** | 3.19*** | 5.28*** | 0.09 | 1.54*** | 0.20 |
| (H3a) | (0.19) | (0.75) | (1.44) | (0.19) | (0.44) | (0.46) |
| External*TMasset | | | | -0.16 | -0.73 | 0.23 |
| *New Entry (H3b) | | | | (0.39) | (0.81) | (0.54) |
| New Trademarks | 0.18*** | 0.58*** | 0.58*** | -0.06 | -0.24** | 0.02 |
| | (0.06) | (0.22) | (0.23) | (0.06) | (0.13) | (0.09) |
| Uni Sector | 0.15*** | 0.47 | 0.61*** | -0.01 | 0.19+ | 0.04 |
| | (0.07) | (0.37) | (0.31) | (0.07) | (0.14) | (0.12) |
| Vertical Integration | 0.13*** | 0.68*** | 0.53*** | -0.14*** | 0.10 | 0.05 |
| | (0.06) | (0.26) | (0.26) | (0.06) | (0.14) | (0.09) |
| Firm Patenting | 0.01 | 0.05 | 0.02 | 0.08*** | 0.17*** | 0.06 |
| | (0.03) | (0.14) | (0.14) | (0.03) | (0.08) | (0.07) |
| Product Patent | -0.09* | -0.18 | -0.28 | 0.07+ | 0.11 | -0.06 |
| | (0.05) | (0.23) | (0.24) | (0.05) | (0.12) | (0.09) |
| BU Size | -0.01 | 0.15 | -0.10 | 0.10** | -0.27*** | -0.26*** |
| | (0.06) | (0.33) | (0.29) | (0.06) | (0.14) | (0.10) |
| Firm Size | 0.02 | -0.11 | 0.07 | -0.08 | -0.09 | -0.03 |
| | (0.07) | (0.39) | (0.35) | (0.07) | (0.16) | (0.13) |
| Firm Start Year | -0.00* | -0.00 | -0.01* | 0.00** | -0.00 | -0.00* |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | 3.72* | | | -3.05* | 2.87 | 2.61 |
| | (2.30) | | | (2.05) | (4.66) | (3.58) |
| | | | | | | |
| Observations | 573 | 563 | 573 | 526 | 536 | 523 |
| R-squared | 0.11 | | | 0.15 | 0.14 | 0.12 |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

### 2.4.4 Robustness

For robustness checks (Table 7), I run the same analysis on an alternative sample and models, focusing only on the binary dependent variables, to address several concerns. First, one important concern about the use of trademarks in this setting is that firms not only file for trademarks for their products but also for the firms themselves. For example, firms frequently file for trademarks to protect their firm names or elements that are related to their names. The presence of firm-level trademarks will contaminate the measure of trademarks related to their products. To address this issue, I further filter the trademarks that are matched to the firms and keep only the trademarks that do not have the firm's name in it. That way, I reduce the possibility of firm-level trademarks in the trademark measure and make the measurement of trademark activity better reflect those that are associated with products or services. With the new trademark measures, the results are consistent with the main analysis. Second, instead of including only standalone-innovator firms, I also include non-standalone firms in the regression analysis to have a more representative sample. This larger sample also provides evidence consistent with the main analysis. Lastly, instead of using the linear probability model, I use the Logit model on the original sample. The Logit model also gives consistent results, as shown in the main analysis.

**Table 7: Robustness: valuable trademarks and external sourcing**

| Dep Var | Ind Var | Whole sample | Logit model | Refined TM |
|---|---|---|---|---|
| External | Topbrand | -0.33*** | -2.59*** | -0.47*** |
| | | (0.11) | (1.04) | (0.14) |
| | TMasset | -0.21*** | -1.05*** | -0.21*** |
| | | (0.07) | (0.39) | (0.09) |
| | TMasset*New entry | 0.76*** | 5.10*** | 1.00*** |
| | | (0.16) | (1.51) | (0.22) |
| Market share increase | External*TMasset | -0.28*** | -1.58*** | -0.26* |
| | | (0.10) | (0.76) | (0.16) |
| | External*TMasset*New entry | -0.37 | 0.00 | 0.13 |
| | | (0.30) | (0.00) | (0.27) |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

## 2.5 Conclusion and Discussion

Previous studies on trademark and external technology sourcing focus on individual industries (Ceccagnoli et al., 2010; Fosfuri et al., 2008) and generate different predictions under different settings. The present study advances this literature by employing a representative sample of all US manufacturing firms and look at the relationship between holding valuable trademarks and the decision to commercialize an external innovation.

A firm's stock of trademark assets is often considered cospecialized complementary assets (Ceccagnoli & Jiang, 2013; Fosfuri & Giarratana, 2009; Fosfuri et al., 2008). The PFI and TCE perspectives offer a set of competing hypotheses regarding the role of complementary assets in encouraging firms to pursue external technology sourcing, and the empirical analysis here supports the TCE perspective. However, this finding does not necessarily go against previous studies supporting the view that firms with complementary assets are at an advantage to acquiring external innovation (e.g., Rothaermel, 2001; Tripsas, 1997). The importance of incumbent firms' complementary assets in enabling them to commercialize external technology is usually tested in empirical settings of radical technological changes or industry emergence. During this time, incumbent firms are likely to have difficulty developing internal innovation. Thus, it is more profitable for them to pursue external innovation. This is also reflected in my analysis that if a firm owns valuable historical trademarks and enters a new industry in which the trademarks are still valuable, it is more likely to commercialize external innovation. Thus, this study suggests that either PFI or TCE dominates under different circumstances.

This study tests only correlations and does not claim any causality per se. However, we have evidence of weak causality based on the time sequence of events. A firm's valuable trademarks are generated over a long period of time, which is likely to have begun before the focal innovation the survey is addressing. Valuable trademarks thus point to a firm-level characteristic that has already been established. The innovative product is generated before 2007 and is commercialized during 2007 to 2009. All questions related to the measure of innovation performance are based on the market performance in 2009, for which the focal innovation represents the most revenue (as the best innovative product). The time sequence for valuable trademarks, innovation, commercialization outcome implies a certain level of causality between these factors. That said, there may be other omitted factors in explaining the observed correlation that are not addressed here.

This study cannot sufficiently address the more general question of whether a firm with cospecialized complementary assets should prioritize internal innovation and only pursue external sourcing when internal innovation is difficult. According to Teece (1986), there are many different types of complementary assets, including manufacturing capabilities, marketing capabilities, and services. Trademarks reflect and correlate only with some of these market-oriented assets. While the "demand side" complementary assets are not easily adaptable to external innovations that bring a different product experience to consumers, other types of complementary assets from the "technology side" or that are related to manufacturing capabilities may not have similar problems. More work needs to be done to gain a better picture of the relationship between complementary assets and external technology sourcing within a non-technological change setting to fully understand firms' technology sourcing strategies.

# 3. Post-Market Entry Capability Development: The Relationship Between Complementary Asset Discontinuity and External Technology Sourcing

In this paper, we ask whether firms reconfigure their complementary assets when they are entering a new industry and commercializing external innovation. Based on the dynamic capabilities framework, it is beneficial for firms to redeploy and reconfigure their complementary assets when the external environment is changing. Thus we expect firms that can change their complementary assets to be more flexible in their routines and will achieve better innovation performance. We identify changes in specific types of complementary assets based on the Division of Innovative Labor survey and look at their correlation with market entry and external sourcing. The results suggest that firms are more likely to change their complementary assets when they are both new entrants and rely on external technology, especially when the firms are young. Changing complementary assets in this context results in better innovation performance, especially when the external innovation is from a startup.

## *3.1 Introduction*

Apple Inc started as a computer company, then enter the smartphone industry using both its own technology and by collaborating with AT&T on communication technologies. Apple's smartphone product, the iPhone, is a huge success in the market and completely shocked the market for mobile phones. One of Apple's senior management once commented that the next company that shocks the smartphone industry is likely not in the smartphone industry already, but come from somewhere else. It is puzzling why a new entrant in an industry, introducing a novel product that partially relies on existing technology in this industry, can be competitive and turn over the market.

The literature on capability development and market entry has identified important features of the entrants' capability profile before entry (Helfat & Lieberman, 2002; Moeen, 2017). Firms that enter a new industry usually possess similar resources and capabilities that are necessary in the new industry (Helfat, 1997; Kim & Kogut, 1996; H. Lee & Shin, 2010), which also help them attain high performance after entry (Cattani, 2005; Dencker, Gruber, & Shah, 2009). After entry, firms often need to develop new capabilities through either organic development or external sourcing to further establish and sustain their competitive advantage (Agarwal & Helfat, 2009; Capron & Mitchell, 2009; Helfat et al., 2007). The literature tells us a lot about firms' choices in internal development and external sourcing of the technical capabilities (Arora, Cohen, et al., 2016; Arora & Gambardella, 1994a; Arora & Merges, 2004; West & Bogers, 2014). However, much less attention is put on the complementary asset discontinuities (Cozzolino & Rothaermel, 2018) and the subsequent development of new complementary assets. The difficulty in measuring specific types of complementary assets further contributes to our lack of understanding in developing complementary assets, because the majority of the existing literature uses a compound measure (Helfat, 1997; Kapoor & Furr, 2015; Moeen, 2017; Rothaermel & Hill, 2005; Tripsas, 1997).

In this study, we focus on whether firms develop new complementary assets as they enter a new industry and introduce innovation products that are based on external technology? The Profiting from Innovation perspective (Teece, 1986, 2006) suggests that firms can leverage their existing complementary assets to commercialize external technology, implying a change in complementary assets may not be necessary. Because our context is also about market entry, we also consider the Dynamic Capabilities perspective (Teece & Pisano, 1994; Teece, Pisano, & Shuen, 1997) that it would be beneficial for firms to reconfigure their existing complementary assets to achieve a better fit with the external innovation and the new industry context – resulting in better innovation performance. We argue that newer firms are more flexible in their routines thus are more likely to change their complementary assets in this context. And that if the external technology is from a startup, it would be even more beneficial for the acquiring firm to reconfigure their complementary assets because they are at a better position in appropriating the returns associated with the startup's innovation.

The empirical analysis is based on the Division of Innovative Labor survey (Arora, Cohen, et al., 2016), which provides information for firms' innovation activities, sources of their innovation, product market entry as well as activities in changing their complementary assets. We look at the correlations between changes in complementary assets, market entry, and external technology sourcing, as well as the performance implications for combining these activities. We show that consistent with the Dynamic Capabilities framework, firms are more likely to implement changes in their complementary assets when they are new entrants and commercializing external innovation. This is especially salient for the firms that are established recently (after the 1980s). Reconfiguring complementary assets as firms enter a new industry and pursue external technology sourcing also results in better innovation outcome, especially when the external technology comes from a startup.

This study contributes to the literature on capability development and technology sourcing in several ways. Different from prior literature on market entry that focuses on the pre-entry capability development (Helfat & Lieberman, 2002; Moeen, 2017), this study seeks to understand post-entry capability development and the relationship between internal development and external sourcing. It digs deeper into the concept of complementary asset discontinuity (Cozzolino & Rothaermel, 2018) and explains under what condition firms may prefer to implement changes in their complementary assets. It also provides a new perspective to our current understanding that firms can leverage their complementary assets to commercialize external innovation (Arora & Ceccagnoli, 2006; Gambardella et al., 2007; Gans & Stern, 2003; Motohashi, 2008) and suggests that it might be beneficial to change their complementary assets as firms enter new industries. The unique survey design (Arora, Cohen, et al., 2016) also enables us to measure changes in different types of complementary assets, which is an advance compared to prior studies (e.g., Helfat, 1997; Moeen, 2017; Tripsas, 1997).

## *3.2 Theoretical framework*

### 3.2.1 Capability development and market entry

Market entry by new or existing (diversifying) firms often happens to firms that possess similar resources and capabilities that are necessary for the new industry (Helfat & Lieberman, 2002). Relevance experiences and capabilities are important determinants of entry (Helfat, 1997; Kim & Kogut, 1996; H. Lee & Shin, 2010). They also have an impact on firm performance after entry (Cattani, 2005; Dencker et al., 2009). In addition, successful entry also requires the entering firm to develop or alter their existing capabilities post-entry (Helfat & Lieberman, 2002).

While there are different types of capabilities identified that are critical to firms' entry choices and sustaining their competitive advantage (Capron & Mitchell, 2009; Moeen, 2017), two types of capabilities are particularly relevant and have received lots of attention by strategy scholars. One is the core technical capabilities (Bayus & Agarwal, 2007; Klepper & Simons, 2000), which means a firm's technical expertise that enables them to succeed in innovation and generate new products in the industry. The other is the complementary capabilities, or complementary assets (Mitchell, 1989; Teece, 1986), which is important for value appropriation following new product introduction. Complementary assets are largely developed from firms' prior operation in similar or related industry contexts (Mitchell, 1989; Rothaermel & Hill, 2005), and have important value during industry transition and technology change (Mitchell, 1989; Tripsas, 1997).

Even though it is critical to have both technical capabilities and complementary assets available, firms do not have to possess them already in house or develop them internally as they enter the new industry. The strategy literature suggests that there are different choices and modes that firms rely on to obtain new capabilities (Agarwal & Helfat, 2009; Helfat et al., 2007). When facing a discontinuity, they don't have to rely on internal development, but also can pursue external sourcing (Helfat, 1994; Rosenkopf & Nerkar, 2001; Vermeulen & Barkema, 2001). And if they pursue external sourcing, they can choose among different modes including service contracts, alliances, or acquisitions, etc. (Arora, Cohen, et al., 2016; Capron & Mitchell, 2009). The growing literature on open innovation and the market for technology (Arora, Cohen, et al., 2016; Arora & Gambardella, 1994a; Arora & Merges, 2004; West & Bogers, 2014) further justify this viable option for firms to pursue external technology sourcing when facing technology discontinuity after entering a new industry.

On the other hand, what we know relatively less is complementary-asset discontinuity – defined as "an advance in which new technologies in manufacturing, distribution, and sales offer superior alternatives in terms of price/performance ratios and efficiency to incumbents' specialized complementary assets that no improvements in the older assets can match the performance of the new ones" (Cozzolino &

Rothaermel, 2018). While there are also many possible options that firms may pursue, in this study, we focus on to what extent do firms develop new complementary assets when they are new entrants in industry and at the same time rely on external technology sourcing for their innovation product.

### 3.2.2 External technology sourcing and complementary assets in the context of market-entry

The Profiting from Innovation (PFI) framework suggests that specialized complementary assets are critical for value capture and value appropriation following a product innovation (Teece, 1986, 2006). As a result, the owner of specialized complementary assets can benefit from innovation generated from other parties. Firms that have the technical capability but do not have the specialized complementary assets are likely to become the technology supplier in the market for technology (Arora & Ceccagnoli, 2006; Gambardella et al., 2007; Gans & Stern, 2003; Motohashi, 2008). On the other hand, incumbent firms can capitalize on their specialized complementary assets and commercialize external innovation to attain high performance (Rothaermel & Hill, 2005; Tripsas, 1997). The availability of different sources of external technology and a vibrant market for technology increases the value of complementary assets for firm performance (Arora & Nandkumar, 2012).

Given the above argument, it is plausible to hypothesize that in the context of market entry, if firms do not have the necessary technical capability – thus need to source it from externally, then they should have a strong position in the necessary complementary assets in order to compete in the new industry. As a result, as these firms try to commercialize external innovation in the new market, they do not need to incur complementary asset discontinuity and make changes in their existing complementary assets.

*H1a. The more likely that firms entering a new industry pursue external technology sourcing, the less likely they will need to adjust their complementary assets in the commercialization stage.*

When firms enter a new industry that they do not previously operate in, even though they are likely to have similar resources or capabilities that can be applied in the new industry (Helfat & Lieberman, 2002), there is still no guarantee that those resources and capabilities can be applied to the new industry context smoothly. If their new product is based on external innovation, it further suggests that the original firms do not have adequate capabilities in house. And the acquired external innovation may not perfectly complement with the firms' existing complementary assets (Bei, 2019).

According to the dynamic capabilities literature (Teece & Pisano, 1994; Teece et al., 1997), one important source of competitive advantage for firms is being able to rapidly build, integrate and reconfigure internal and external competencies, including the resources, organization skills, and functional competencies in response to a changing industry context. Furthermore, Pisano (2017) points out that the core of this reconfiguration process requires the firms' capability search strategies which enable them to choose to invest in different types of capabilities. Considering the case of

Penrosian diversification: the original Penrosian growth theory (Penrose, 1959) suggests that firms excess resource investment in the initial market provides opportunities to use them in a new market and spread the fixed cost of the initial investment, supporting the related diversification scheme (Helfat & Eisenhardt, 2004; Montgomery & Wernerfelt, 1988). Pisano's (2017) framework deviates from this view and proposes that the creation of new market-specific capabilities is critical during the diversification process.

This discussion in the dynamic capabilities literature informs our analysis in that, as firms enter new markets, efficiently redeploy and create necessary capabilities and resources can help them better address the market needs and gain competitive advantage. When they are commercializing external innovations, it is also important that they adjust their complementary assets to fit with both the new market and the external technology. As a result, we expect to see more complementary asset discontinuity and efforts in changing their complementary assets.

*H1b. The more likely that firms entering a new industry pursue external technology sourcing, the more likely they will reconfigure their complementary assets in the commercialization stage.*

### 3.2.3 Firms with flexibility are likely to implement complementary asset discontinuity

According to the Dynamic Capabilities framework, firms are better off if they can reconfigure their existing complementary assets to match the new market, when they are entering the new market to commercialize an external technology. If this is true, then we expect to see more changes in firms' complementary assets in this context when the firms are more flexible in their existing capabilities.

Winter (2003) defines capabilities as collections of routines that organizations follow to perform certain activities repetitively. The routines/capabilities that firms possess can be general purpose or market-specific, and firms can choose to either deepen their existing routines or broadening their repertoire of routines to incorporate new ones. The latter is usually needed for firms to be able to compete in new markets (G. P. Pisano, 2017). Organizational capabilities and routines are evolutionary (Nelson & Winter, 1982). They emerge as the result of extensive search and experimentation and are path dependent and subject to inertia pressures. Because of the uncertain process of search and experimentation, newly formed routines are more flexible and can subject to changes when necessary, while long existed routines may be more rigid and refuse to change. We propose to further test this difference in flexibility by looking at relatively newer versus older companies, assuming that newer companies are more likely to flexible and are willing to change their routines/capabilities when necessary.

*H2. The more likely that firms entering a new industry pursue external technology sourcing, the more likely they will reconfigure their complementary assets in the commercialization stage if they are newer firms.*

### 3.2.4 Performance implications for complementary asset discontinuity when commercializing external innovation after market entry

As we discussed previously, according to the Dynamic Capabilities framework, firms are better off if they can reconfigure their existing complementary assets to match the new market, when they are entering the new market to commercialize an external technology. Being able to change existing capabilities and develop new capabilities that better fit with the new market can enable the firms to obtain a competitive advantage compared to the other firms in the new market (G. P. Pisano, 2017). It also provides an opportunity to “disrupt” the existing complementary assets in that market, so that existing firms in the market are not able to compete efficiently without reconfiguring their existing complementary assets – even if they can produce the same innovation product. As a result, we expect to see better innovation performance when firms are new entrants in an industry, commercializing external innovation, at the same time reconfigure their complementary assets to generate new ones.

*H3. Firms are likely to have better innovation performance if they are entering a new industry and pursuing external technology sourcing, at the same time reconfigure their complementary assets.*

### 3.2.5 The case for sourcing technology from startups

Startups is a unique group of technology suppliers. We argue here that when the external technology is obtained through a startup, the performance implications for firms that are able to reconfigure their complementary assets for the commercialization is even more salient.

According to Gans and Stern (2003), with the presence of a "market for ideas," technology entrepreneurs are likely to become technology suppliers when they do not have the necessary complementary assets to commercialize the innovation. Thus the acquiring firm that can provide the specialized complementary assets to commercialize the technology is expected to better capture the value generated by the new technology.

Also, obtaining external technology from startups is usually combined with acqui-hiring or employee movement (Bei, 2018; Chatterji & Patro, 2014), which ensures that the acquiring firm obtains the necessary technical capability when needed. This specific characteristics of obtaining technology from startups make the subsequent development of the technology less risky compared to getting it from other companies, contractors, or public institutions (Arora, Cohen, et al., 2016).

As a result, if the acquiring firms can provide the specialized complementary assets that are compatible with the startup's technology and also with the new market needs, they are at a better position to fully capture the value created by the original innovation.

*H4. Firms are likely to have better innovation performance if they are entering a new industry and commercialize external innovation from startups (compared to from other external sources), at the same time reconfigure their complementary assets.*

## 3.3 Data and methods

### 3.3.1 Sample

The empirical analysis of this study is based on a sample of manufacturing firms in the "division of innovative labor" (DoIL) survey (Arora, Cohen, et al., 2016). The survey was conducted in 2010 at the business unit level of firms and collected information for their new product introductions during the year 2007 through 2009. The sampling frame for the survey was the Dun and Bradstreet (D&B) Selectory database. The sample was stratified along multiple dimensions, including industry, size, and whether the respondent is an entrepreneurial firm. Categories such as large firms, startup firms, firms from more innovative industries are oversampled. And the sample is further reweighted with post-sample weights based on the Census data to ensure representativeness of the whole population. Unless otherwise specified, sample weights are applied throughout the analysis. For further details regarding the sampling process, phone survey procedures, response rates and tests of response bias, please refer to Arora et al. (2016).

The original survey samples all American manufacturing firms, and is not exclusively on innovators or R&D performers, as several of the other earlier surveys do (e.g., Cohen, Nelson, & Walsh, 2000; Levin, Klevorick, Nelson, & Winter, 1987). The survey collected information on the respondent's most significant innovation products during the year 2007 to 2009. Respondents need to provide information for whether they had introduced any new product during that period, and also whether the new product is new-to-the-market or new-to-the-firm. The survey questionnaire also collects information regarding: (1) the source and channel of the innovation; (2) whether the firm is new entrant to the focal industry; (3) whether the firm develops new sales and distribution channels to commercialize the innovation; (4) whether the firm purchases new equipment, hire employees with new skills; (5) whether the firm perform any process innovation; (6) different ways of assessing the innovation outcome. These data are super valuable and enable this study to look at firms' innovation activity and their investments in developing new complementary assets.

Further development of the dataset follows Bei (2019) and Arora et al. (2016) to incorporate information from secondary datasets. Trademark activities are included as an additional indication of complementary assets development. Patent activities are included as a control. And firm-level information such as diversification, size, year of establishment is collected from the National Establishment Time Series (2013) dataset.

In this study, I focus on a subsample of firms that generate new-to-the-market innovation and look at their activities in market entry, external technology sourcing, and further capability development for the commercialization of the innovation. The definition of the innovator firms that generate new-to-the-market innovation follows Arora et al. (2016) and exclude firms that "reported either that they introduced their most significant innovation outside of the 2007-2009 time window, or reported zero 2009 sales revenue due to this innovation". The final sample consists of 911 innovator firms. In each of the analysis, the actual number of observation may change depending on the availability of the survey-based variables.

### 3.3.2 Measurement of complementary asset discontinuity

Because capabilities and experiences are closely related, the studies on capabilities – a very abstract construct – usually use experience to measure capabilities. The measurement for capabilities underwent an evolutionary process. Earlier studies use size, industry participation, product types to measure the broadly defined capability (Klepper & Simons, 2000; Mitchell, 1989). As scholars make a more clear distinction of technical capabilities, complementary knowledge, and complementary assets, more specific activity-based measures are developed. The measurement of complementary assets is more context-dependent and less specific to different subcategories of complementary assets. Moeen (2017) use the number of protected plant varieties granted to a firm in the preceding four years to measure complementary assets. In a similar vein, Helfat (1997) uses coal reserves in the synthetic fuels industry; Tripsas (1997) uses font libraries in the typesetter's industry; Rothaermel and Hill (2005) use switching networks in the telecommunications industry; and Kapoor and Furr (2015) use deposition surfaces in the solar cells industry. Mitchell (1992) use prior year industry market share to measure market-related capabilities. Arora and Nandkumar (2012) use the number of sales executives employed at the time of entry to measure marketing capabilities.

As defined in Teece's (1986) original work, there are different types of complementary assets/capabilities: specialized manufacturing capability, access to distribution channels, service networks, and complementary technologies, etc. While all of them can be captured by the number of specific product lines within an industry, as mentioned above, it does not distinguish between these different types. At the same time, these different types of complementary assets are drastically different from each other and have different implications for firm strategy. Furthermore, the previous measures complementary assets make it very difficult to track and record changes in complementary assets – and especially complementary asset discontinuity.

Thanks to the survey design by Arora et al. (2016), we can measure changes in firms' several different complementary assets and study their correlation with firms' innovation activity. In the empirical analysis, we first look at changes in these complementary assets as the dependent variable to study under what condition are firms likely to make changes in their complementary assets. Then, we look at the innovation performance and see how these changes in complementary assets (as independent variables) are correlated with innovation performance.

### 3.3.3 Dependent variables

#### 3.3.3.1 Measurements for complementary assets

*Changes in sales and distribution (Sale/Dist):* The survey respondents were asked whether they "develop new sales and distribution channels" to commercialize their focal innovation. This is used to build an indicator variable to measure whether the firms have implemented a change in sales and distribution channels as one type of complementary asset.

*New equipment or employee skills (Equip/Skill):* The survey respondents were asked whether they "buy new types of equipment or hire employees with skills different from existing employees" to commercialize their focal innovation. This is used to build an indicator variable to measure whether the firms have implemented a change in equipment or employee skills as one type of complementary asset.

*New trademarks:* The survey is matched to the USPTO trademark dataset to collect the respondents' innovation activity (Bei, 2019). Based on the matched trademark information, an indicator is created indicating whether the firms have filed for any new trademarks from 2006 to 2010. Filing for new trademarks is an indication of implementing a change in this specific type of complementary asset.

Process innovation (Proc Inno): The survey respondents are also asked whether they "introduced any new or significantly improved processes for making a product or delivering a service". This is used to build an indicator variable to measure whether the firms have implemented new changes in their manufacturing process as one type of complementary asset.

#### 3.3.3.2 Measurements for innovation performance

Following Bei (2019), I use three different measures of innovation performance to infer the outcome of the respondents' innovation effort. These measures are also based on the survey questions.

*Changes in market share:* The survey respondents were asked about their changes in market share over the sample period of 2007-2009. The answers could be either a dummy variable indicating whether there is an increase in market share or not, or a percentage of the estimated change in their market share. In this study, we use the absolute change in market share (log-transformed) as an indicator of innovation performance.

*Percentage of total sales:* The survey provides information on the estimated percentage of total sales in 2009 that comes from the respondents' focal innovation, which is used as an alternative measure of innovation outcome.

*Ratio of innovation sales:* This measure is created by taking the ratio of the percentage sale of their focal innovation over the percentage sale of their all innovation during the survey period. This measure provides information regarding the importance of this focal innovation among the firms' all other innovation activities.

#### 3.3.3.3 Independent variables

*External innovation:* The survey has a series of questions about the sources and channels of the respondents' focal innovation. There is a list of multiple choices that firms can choose from, including suppliers, customers, other firms in the industry, consulting service providers, independent inventors, or universities. Following Arora et al. (2016), If the respondents indicated any of these external sources as the source of their focal innovation, then it is labeled as an external innovation. Otherwise, it is labeled as an internal innovation.

*New entrant of industry:* The survey has a question asking "whether the firm had entered the specified industry for less than five years." Following Bei (2019), this question is used to create an indicator variable of whether the respondent is a new entrant to the industry.

**3.3.3.4 Control variables**

*Product patent:* One of the survey questions asks whether the respondent patented any part of the innovation. It is used to generate an indicator variable of the product level patenting activity.

*Business unit (BU) size:* Business units are defined as activities within a given NAICS industry within a firm. The survey respondents are asked to provide the number of employees in the focal industry, which is used as a measure for the business unit size.

*Firm size:* the measurement of firm size is based on the data from the Dun & Bradstreet, using the count of the total number of employees at all sites.

*Industry-fixed effect:* Following Bei (2019), the industry-fixed effect is reported at the three-digit NAICS code level. There are 21 NAICS-3 industries in the sample.

*Firm patenting:* Firm-level patenting information is from the PATSTAT patent database marched to the survey respondents. The total count of patents filed after 2000 is collected and log-transformed.

*Single sector firms:* This is an indicator variable that measures the level of diversification of the parent firm. The data is obtained from the NETS database as the total count of the number of sectors that the parent firm operates in.

*Vertical integration:* The measurement of vertical integration is based on the survey question asking, "is there another division or business is one of your main customers/suppliers?" An indicator variable is generated if the answer is yes to either customers or suppliers.

*Firm start year:* Following Bei (2018), information for the firms' year of establishment is from the NETS database and based on the definition of the 2010 firms. This variable is used to control for firm age.

### 3.3.4 Estimation methods

To perform regression analysis on the survey data, I use the STATA commands for survey design, *svyset* and a series of compatible commands for regression analysis under *svyset* (Judkins, 1990). Because the empirical analyses focus on firms that introduced new-to-the-market innovation products, it is a subgroup of the original survey sample. To ensure the representativeness of the survey sample, the subpopulation option is used across the analysis to ensure the correct calculation of the variance of an estimate. Linear probability model and ordinary least square are used for the regression analysis. And industry fixed effect at the three-digit NAICS level is employed across the analysis.

### 3.3.5 Data description

Table 8 shows the summary statistics for the sample of analysis. Table 9 shows the correlation table. The summary statistics are based on all firms that introduced a new-to-the-market innovation product in the original survey sample, which is also for the main analysis. Variation in the number of observations represents the availability of responses of the corresponding questions.

**Table 8: Summary statistics**

| | Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| (1) | Trademark | 911 | 0.58 | 0.49 | 0 | 1 |
| (2) | Sale/Dist | 910 | 0.34 | 0.48 | 0 | 1 |
| (3) | Equip/Skill | 905 | 0.46 | 0.50 | 0 | 1 |
| (4) | Proc Inno | 898 | 0.71 | 0.45 | 0 | 1 |
| (5) | External | 911 | 0.49 | 0.50 | 0 | 1 |
| (6) | Entrant | 911 | 0.06 | 0.24 | 0 | 1 |
| (7) | Market share increase | 699 | 0.92 | 2.70 | -4.61 | 6.21 |
| (8) | % sales | 831 | 2.26 | 1.07 | 1.10 | 4.32 |
| (9) | % innovation sales | 805 | -0.49 | 0.89 | -2.99 | 3.22 |
| (10) | Single industry | 911 | 0.47 | 0.50 | 0 | 1 |
| (11) | Vertical integration | 911 | 0.34 | 0.47 | 0 | 1 |
| (12) | Firm patent | 911 | 1.14 | 1.74 | 0.00 | 9.26 |
| (13) | Product patent | 911 | 0.54 | 0.50 | 0 | 1 |
| (14) | BU size | 911 | 2.37 | 1.03 | 0.48 | 5.48 |
| (15) | Firm size | 911 | 2.52 | 1.21 | 1.00 | 5.62 |
| (16) | Firm age | 911 | 1970.27 | 33.98 | 1837 | 2009 |

**Table 9: Correlation matrix**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.00 | | | | | | | | | | | | | | | |
| (2) | -0.08 | 1.00 | | | | | | | | | | | | | | |
| (3) | 0.03 | 0.17 | 1.00 | | | | | | | | | | | | | |
| (4) | 0.05 | 0.10 | 0.23 | 1.00 | | | | | | | | | | | | |
| (5) | 0.05 | 0.02 | 0.06 | 0.04 | 1.00 | | | | | | | | | | | |
| (6) | 0.02 | 0.19 | 0.02 | 0.05 | 0.04 | 1.00 | | | | | | | | | | |
| (7) | -0.05 | 0.10 | 0.10 | 0.07 | 0.03 | 0.15 | 1.00 | | | | | | | | | |
| (8) | -0.20 | 0.14 | 0.10 | 0.06 | 0.02 | 0.12 | 0.22 | 1.00 | | | | | | | | |
| (9) | -0.09 | 0.00 | 0.01 | 0.00 | -0.04 | -0.03 | 0.04 | 0.53 | 1.00 | | | | | | | |
| (10) | -0.41 | 0.21 | -0.05 | -0.11 | 0.01 | 0.09 | 0.11 | 0.23 | 0.08 | 1.00 | | | | | | |
| (11) | 0.14 | -0.05 | 0.05 | 0.06 | 0.08 | -0.05 | -0.09 | -0.07 | -0.07 | -0.13 | 1.00 | | | | | |
| (12) | 0.46 | -0.13 | 0.06 | 0.11 | 0.04 | -0.09 | 0.03 | -0.09 | -0.09 | -0.39 | 0.15 | 1.00 | | | | |
| (13) | 0.29 | 0.02 | 0.13 | 0.13 | -0.02 | 0.05 | 0.08 | 0.01 | -0.07 | -0.14 | 0.03 | 0.35 | 1.00 | | | |
| (14) | 0.50 | -0.14 | 0.13 | 0.13 | 0.01 | -0.12 | -0.10 | -0.28 | -0.18 | -0.57 | 0.27 | 0.55 | 0.27 | 1.00 | | |
| (15) | 0.56 | -0.19 | 0.09 | 0.13 | 0.04 | -0.12 | -0.13 | -0.25 | -0.12 | -0.66 | 0.23 | 0.62 | 0.22 | 0.82 | 1.00 | |
| (16) | -0.18 | 0.11 | -0.05 | -0.05 | -0.01 | 0.16 | 0.11 | 0.14 | 0.03 | 0.36 | -0.11 | -0.23 | 0.00 | -0.33 | -0.41 | 1.00 |

## 3.4 Results

### 3.4.1 Firms are likely to develop new complementary assets when they enter new industry and commercialize external innovation

We are concerned with whether firms would develop new complementary assets if they are new entrants in an industry and pursuing external technology sourcing. In the theory section, we argue that the PFI framework (Teece, 1986, 2006) and the Dynamic Capabilities framework (Teece & Pisano, 1994; Teece et al., 1997) offers different implications regarding the likelihood of developing new complementary assets under this situation. We test these competing hypotheses by looking at four different types of complementary assets: new sales and distribution channel, new equipment or employee skills, new trademarks and new process innovation. Each of these complementary assets is represented by a survey question as a 0/1 variable, and we look at the interaction term between external innovation and new entrants to see whether firms are more likely to develop the corresponding complementary assets by looking at the regression coefficient.

The regression results are shown in Table 10. Column 1 looks at the development of new sales and distribution channels and suggests that firms that are new entrants and utilize external innovation are 24 percent more likely to develop new sales and distribution channels in their commercialization process. In Column 2, firms that are new entrants and utilize external innovation are 41 percent more likely to develop new equipment and hire employees with new skills. For trademarks in Column 3, the coefficient suggests a 19 percent increase. The coefficients are strongly significant for new equipment and employee skills, and weakly significant for new sales and distribution channels, or new trademarks. For process innovation in Column 4, the coefficient is not significantly different from zero but still shows a positive value. The coefficients are not significant for either external innovation or new entrant by themselves, except for new trademarks.

These analyses are based on the correlation between new developments of complementary assets and firms' activity in entry and external sourcing. The results suggest that firms are indeed more likely to invest in and reconfigure their complementary assets as they involve in both new entry and external technology sourcing. Thus the Dynamic capabilities framework is supported.

### 3.4.2 Firms that are more flexible in resource redeployment are more likely to change their complementary assets

In the second hypothesis, we submit that, if conforming to the dynamic capabilities view that firms benefit from reconfiguring their capabilities and complementary assets, then the more flexible firms are with their routines, the more likely they will make the changes when necessary. We test this hypothesis by splitting the whole sample into two subsamples by firm age, with a cutoff year of 1980. New firms are likely to have more flexible routines and suffer less from rigidity pressure, so they are the ones that are more likely to change their complementary assets in response to a more dynamic environment. On the contrary, old firms would be deeply rooted in their routines and are less flexible in changes.

**Table 10: New development in complementary assets as firms enter a new industry and commercialize external innovation**

| VARIABLES | (1) Sale/Dist | (2) Equip/Skill | (3) Trademark | (4) Proc Inno |
|---|---|---|---|---|
| External | 0.00 | -0.01 | 0.06* | -0.01 |
| | (0.04) | (0.05) | (0.04) | (0.05) |
| Entrant | 0.16 | -0.15 | 0.03 | 0.01 |
| | (0.13) | (0.12) | (0.11) | (0.12) |
| Ext*Ent | 0.24+ | 0.41*** | 0.19+ | 0.16 |
| | (0.17) | (0.18) | (0.14) | (0.15) |
| Single Ind | 0.03 | 0.05 | -0.07+ | -0.06 |
| | (0.05) | (0.06) | (0.05) | (0.06) |
| Vertical integrate | 0.07+ | 0.06 | 0.01 | -0.02 |
| | (0.05) | (0.05) | (0.04) | (0.05) |
| Total patent | -0.00 | 0.01 | 0.07*** | -0.01 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Prod patent | 0.11*** | 0.13*** | 0.09*** | 0.06 |
| | (0.05) | (0.05) | (0.04) | (0.05) |
| BU size | -0.01 | 0.07** | 0.04 | 0.10*** |
| | (0.05) | (0.04) | (0.04) | (0.05) |
| Firm size | -0.06+ | -0.06+ | 0.15*** | -0.03 |
| | (0.05) | (0.04) | (0.04) | (0.04) |
| Firm age | -0.00 | -0.00 | 0.00*** | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | 0.52 | 1.77 | -2.58*** | 0.10 |
| | (1.64) | (1.72) | (1.22) | (1.85) |
| Observations | 910 | 905 | 911 | 898 |
| R-squared | 0.12 | 0.09 | 0.30 | 0.06 |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

**Table 11: Subsample of new and old firms in the likelihood of implementing changes in complementary assets**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Sale/Dist | | Equip/Skill | | Trademark | | Proc Inno | |
| | Recent | Old | Recent | Old | Recent | Old | Recent | Old |
| External | -0.03 | 0.05 | 0.03 | -0.07 | 0.07 | 0.10** | -0.09* | 0.14*** |
| | (0.06) | (0.06) | (0.06) | (0.07) | (0.06) | (0.05) | (0.06) | (0.06) |
| Entrant | 0.14 | 0.14 | -0.13 | -0.03 | 0.01 | 0.13 | -0.07 | -0.14 |
| | (0.14) | (0.31) | (0.14) | (0.33) | (0.11) | (0.16) | (0.13) | (0.21) |
| External * Entrant | 0.39*** | -0.29 | 0.44*** | 0.17 | 0.25* | -0.15 | 0.28* | 0.03 |
| | (0.17) | (0.47) | (0.20) | (0.46) | (0.15) | (0.23) | (0.17) | (0.27) |
| Single Ind | 0.10* | -0.03 | 0.07 | 0.11 | -0.13** | -0.01 | 0.05 | -0.15*** |
| | (0.07) | (0.08) | (0.07) | (0.08) | (0.07) | (0.07) | (0.08) | (0.08) |
| Vertical integrate | 0.07 | 0.08 | 0.07 | 0.06 | 0.02 | -0.01 | 0.07 | -0.09+ |
| | (0.07) | (0.07) | (0.06) | (0.07) | (0.06) | (0.06) | (0.07) | (0.07) |
| Total patent | -0.01 | 0.01 | 0.05** | -0.04* | 0.09*** | 0.04*** | -0.03 | 0.02 |
| | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) |
| Prod patent | 0.14*** | 0.03 | 0.11** | 0.14** | 0.06 | 0.12** | 0.11** | 0.01 |
| | (0.06) | (0.07) | (0.06) | (0.07) | (0.05) | (0.06) | (0.06) | (0.07) |
| BU size | 0.02 | -0.05 | 0.11*** | 0.05 | 0.07+ | 0.01 | 0.03 | 0.15*** |
| | (0.06) | (0.07) | (0.05) | (0.06) | (0.05) | (0.05) | (0.07) | (0.06) |
| Firm size | -0.04 | -0.06 | -0.12*** | 0.03 | 0.08* | 0.22*** | 0.04 | -0.06 |
| | (0.06) | (0.07) | (0.06) | (0.06) | (0.06) | (0.05) | (0.07) | (0.05) |
| Firm age | -0.00 | -0.00 | -0.00 | -0.00 | 0.00 | 0.00*** | 0.00 | 0.00+ |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | 4.22 | 2.93 | 0.43 | 1.01 | -6.02 | -4.54*** | -5.97 | -2.45 |
| | (6.96) | (2.53) | (7.07) | (2.72) | (6.51) | (2.05) | (8.49) | (2.25) |
| Observations | 491 | 419 | 491 | 414 | 492 | 419 | 488 | 410 |
| R-squared | 0.13 | 0.19 | 0.12 | 0.15 | 0.29 | 0.38 | 0.09 | 0.21 |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

In Table 11, we show the regression analysis on the subsamples by looking at the same four different complementary assets. The coefficients for new firms are positive and significant for all four complementary assets. When being new entrants in an industry and trying to commercialize external innovation, new firms are 39 percent more likely to develop new sales and distribution channels; 44 percent more likely to develop new equipment and hire new employees with new skills; 25 percent more likely to file for new trademarks; and 28 percent more likely to perform process innovation. On the other hand, the coefficients for the old firms are not significantly different from zero for all four complementary assets. The difference between the coefficients is also remarkable. While the point of this analysis is not to compare the new or old firms, we do show some evidence that for newer firms, changing their complementary assets is an optimal choice as they enter a new industry and pursue external technology sourcing. Thus hypothesis 2 is supported.

### 3.4.3 Performance implications for firms that reconfigure complementary assets as they enter a new industry and commercialize external innovation

In this part of the analysis, we look at each of the four complementary assets separately and look at three different measures of innovation performance to assess the innovation outcome. Based on the dynamic capability framework (Teece & Pisano, 1994; Teece et al., 1997), firms that can redeploy their resources and capabilities in response to the changing external environment are expected to have better performance. Due to the data limitation of this study, we are looking for positive correlations on the three-way interaction between complementary asset changes, being a new entrant, and external sourcing. But we do not necessarily expect to see positive coefficients in all three measures of innovation performance.

In Table 12, columns 1 through 3, we are looking at changes in sales and distribution channels. The coefficients are positive and significant for the three-way interaction for market share increase and percentage of total sales – suggesting there is indeed a positive return to being able to reconfigure their sales and distribution effort. In columns 4 through 6, we are looking at changes in equipment and employee skills. We do not see any significant positive correlation for all three measures of innovation performance.

In Table 13, columns 1 through 3, we are looking at new trademark filings. Again, we do not see any significant positive correlation for all three measures of innovation performance. This is not surprising because trademarks are more valuable as they age and are associated with certain product image (Bei, 2019). Thus new trademarks do not carry much value at all. In columns 4 through 6, we are looking at process innovation. The coefficients are positive and weakly significant for the three-way interaction for market share increase and percentage of innovation sales – suggesting a positive return to being able to reconfigure their manufacturing process.

**Table 12: Innovation performance for firms that reconfiguring complementary assets as they enter a new industry and commercialize external innovation (I)**

| VARIABLES | (1) MSinc | (2) %sale | (3) %inno | (4) MSinc | (5) %sale | (6) %inno |
|---|---|---|---|---|---|---|
| | Sale/Dist | Sale/Dist | Sale/Dist | Equip/Skill | Equip/Skill | Equip/Skill |
| CA discontinuity | -0.43 | 0.06 | -0.07 | 0.47 | 0.20+ | 0.16 |
| | (0.43) | (0.14) | (0.11) | (0.42) | (0.15) | (0.13) |
| Entrant | 2.77*** | 0.49*** | -0.33 | 0.73 | 0.54*** | 0.08 |
| | (0.58) | (0.25) | (0.30) | (1.47) | (0.26) | (0.28) |
| CA*Ent | -2.21** | -0.37 | 0.06 | 0.53 | -0.65 | -0.91+ |
| | (1.15) | (0.51) | (0.58) | (1.60) | (0.70) | (0.69) |
| External | 0.24 | -0.10 | -0.08 | 0.49+ | -0.06 | 0.07 |
| | (0.36) | (0.13) | (0.11) | (0.37) | (0.14) | (0.12) |
| CA*Ext | 0.66 | 0.10 | 0.01 | -0.01 | 0.00 | -0.31** |
| | (0.62) | (0.21) | (0.17) | (0.62) | (0.21) | (0.18) |
| Ent*Ext | -3.24*** | -0.46 | 0.79** | -0.46 | -0.24 | 0.14 |
| | (1.52) | (0.36) | (0.46) | (1.77) | (0.46) | (0.39) |
| CA*Ent*Ext | 4.57*** | 1.04* | -0.60 | 1.08 | 1.07 | 0.62 |
| | (1.91) | (0.67) | (0.73) | (1.98) | (0.87) | (0.80) |
| Single Ind | 0.06 | 0.13 | -0.01 | 0.03 | 0.13 | -0.01 |
| | (0.36) | (0.13) | (0.12) | (0.37) | (0.13) | (0.12) |
| Vertical integrate | -0.81*** | 0.02 | 0.04 | -0.80*** | 0.03 | 0.05 |
| | (0.32) | (0.11) | (0.10) | (0.31) | (0.12) | (0.10) |
| Total patent | 0.28*** | 0.08* | 0.02 | 0.27*** | 0.09** | 0.02 |
| | (0.10) | (0.05) | (0.05) | (0.10) | (0.05) | (0.05) |
| Prod patent | 0.60*** | 0.11 | -0.07 | 0.50** | 0.10 | -0.06 |
| | (0.29) | (0.11) | (0.08) | (0.29) | (0.11) | (0.09) |
| BU size | 0.40** | -0.27*** | -0.21*** | 0.37* | -0.29*** | -0.23*** |
| | (0.24) | (0.10) | (0.08) | (0.23) | (0.10) | (0.08) |
| Firm size | -0.59*** | -0.08 | 0.06 | -0.56*** | -0.07 | 0.08 |
| | (0.23) | (0.10) | (0.09) | (0.23) | (0.10) | (0.09) |
| Firm age | 0.01*** | 0.00 | -0.00 | 0.01*** | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -23.37*** | 0.62 | 0.79 | -23.47*** | 0.51 | 0.87 |
| | (9.45) | (3.69) | (3.44) | (9.16) | (3.75) | (3.42) |
| Observations | 698 | 830 | 804 | 698 | 830 | 804 |
| R-squared | 0.17 | 0.11 | 0.08 | 0.17 | 0.12 | 0.09 |

Standard errors in parentheses
*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$

**Table 13: Innovation performance for firms that reconfiguring complementary assets as they enter a new industry and commercialize external innovation (II)**

| VARIABLES | (1) MSinc | (2) %sale | (3) %inno | (4) MSinc | (5) %sale | (6) %inno |
|---|---|---|---|---|---|---|
| | Trademark | Trademark | Trademark | Proc Inno | Proc Inno | Proc Inno |
| CA discontinuity | -0.04 | -0.13 | 0.09 | 0.67* | 0.20+ | 0.10 |
| | (0.42) | (0.15) | (0.13) | (0.41) | (0.15) | (0.12) |
| Entrant | 0.79 | 0.04 | -0.55 | 2.56*** | 0.33 | 0.06 |
| | (1.16) | (0.39) | (0.44) | (0.70) | (0.38) | (0.20) |
| CA*Ent | 0.62 | 0.75+ | 0.90* | -2.06** | -0.14 | -0.48 |
| | (1.22) | (0.57) | (0.55) | (1.22) | (0.57) | (0.50) |
| External | 0.67** | 0.04 | -0.05 | 0.66+ | -0.11 | 0.04 |
| | (0.38) | (0.14) | (0.11) | (0.46) | (0.18) | (0.14) |
| CA*Ext | -0.56 | -0.26+ | -0.09 | -0.29 | 0.04 | -0.17 |
| | (0.56) | (0.20) | (0.18) | (0.57) | (0.22) | (0.18) |
| Ent*Ext | 1.32 | 0.54 | 0.44 | -1.77 | 0.26 | -0.39 |
| | (1.28) | (0.65) | (0.53) | (1.81) | (0.66) | (0.46) |
| CA*Ent*Ext | -1.29 | -0.55 | -0.73 | 2.78+ | 0.14 | 0.91+ |
| | (1.52) | (0.84) | (0.69) | (2.13) | (0.84) | (0.69) |
| Single Ind | 0.01 | 0.12 | -0.01 | 0.06 | 0.15 | -0.01 |
| | (0.37) | (0.13) | (0.12) | (0.37) | (0.13) | (0.12) |
| Vertical integrate | -0.71*** | 0.05 | 0.03 | -0.72*** | 0.04 | 0.03 |
| | (0.32) | (0.11) | (0.10) | (0.31) | (0.11) | (0.10) |
| Total patent | 0.29*** | 0.10** | 0.02 | 0.28*** | 0.07+ | 0.03 |
| | (0.10) | (0.05) | (0.05) | (0.11) | (0.05) | (0.05) |
| Prod patent | 0.58** | 0.13 | -0.09 | 0.55** | 0.12 | -0.07 |
| | (0.29) | (0.11) | (0.09) | (0.28) | (0.11) | (0.09) |
| BU size | 0.39** | -0.26*** | -0.21*** | 0.39* | -0.30*** | -0.22*** |
| | (0.23) | (0.11) | (0.08) | (0.25) | (0.10) | (0.08) |
| Firm size | -0.52*** | -0.04 | 0.06 | -0.64*** | -0.07 | 0.07 |
| | (0.24) | (0.11) | (0.09) | (0.25) | (0.10) | (0.09) |
| Firm age | 0.01*** | 0.00 | -0.00 | 0.01*** | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -24.53*** | -0.07 | 0.84 | -22.79*** | 0.26 | 1.25 |
| | (9.40) | (3.74) | (3.44) | (9.26) | (3.91) | (3.47) |
| | | | | | | |
| Observations | 699 | 831 | 805 | 693 | 821 | 796 |
| R-squared | 0.17 | 0.12 | 0.08 | 0.17 | 0.12 | 0.08 |

Standard errors in parentheses
*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$

In sum, the analysis in this part does show some evidence of firms being better off by altering their existing complementary assets as they enter new industries and commercialize external innovation. All though in practice, we need to be more careful when we think about specific types of complementary assets, because they may not benefit equally from complementary asset discontinuity.

### 3.4.4 Comparing external sourcing from startups versus other sources

In the last analysis, we consider that startups have unique features that help with the sourcing firms' value capture effort. And it would be especially beneficial if the sourcing firm is able to reconfigure their complementary assets to further protect their competitive advantage in the externally acquired innovation. For this analysis, we look at the subsample of firms that obtain external innovations, eliminating the ones that develop their innovation internally. And instead of looking at the indicator for external sourcing, here we look at the indicator of startups, leaving the control group as innovation obtained through other sources.

In Table 14 and 15, we can see that there is indeed a positive coefficient on the three-way interaction for the percentage of total sales and the percentage of innovation sales measure. And this is true for three of the complementary asset measures: changes in sales and distribution, changes in equipment and employee skills, and changes in the manufacturing process. For changes in new trademarks, the coefficient is significantly positive only for the percentage of total sales.

**Table 14: Innovation performance for acquiring external innovation from startups vs other external sources (I)**

| VARIABLES | (1)<br>MSinc | (2)<br>%sale | (3)<br>%inno | (4)<br>MSinc | (5)<br>%sale | (6)<br>%inno |
|---|---|---|---|---|---|---|
| | Sale/Dist | Sale/Dist | Sale/Dist | Equip/Skill | Equip/Skill | Equip/Skill |
| Entrant | -0.02 | -0.07 | 0.63* | 0.19 | 0.03 | 0.32 |
| | (1.47) | (0.29) | (0.39) | (1.14) | (0.36) | (0.35) |
| CA discontinuity | -0.02 | 0.12 | -0.01 | 0.35 | 0.10 | -0.10 |
| | (0.46) | (0.17) | (0.13) | (0.45) | (0.16) | (0.14) |
| CA*Ent | 2.66*** | 0.75*** | -0.21 | 3.13*** | 0.87*** | -0.23 |
| | (0.43) | (0.34) | (0.31) | (0.46) | (0.34) | (0.36) |
| Startup | 1.55*** | -0.03 | 0.09 | 1.19*** | -0.14 | 0.26 |
| | (0.60) | (0.34) | (0.21) | (0.56) | (0.32) | (0.22) |
| CA*Startup | -0.24 | 0.23 | 0.05 | 0.29 | 0.46 | -0.26 |
| | (0.82) | (0.44) | (0.29) | (0.73) | (0.43) | (0.29) |
| Ent*Startup | 0.00 | 0.00 | 0.00 | 1.44 | 1.72*** | -0.25 |
| | (0.00) | (0.00) | (0.00) | (1.36) | (0.52) | (0.43) |
| CA*Ent*Startup | -1.13+ | 1.20*** | 0.64** | -0.91 | 1.38*** | 0.56+ |
| | (0.85) | (0.52) | (0.37) | (0.95) | (0.51) | (0.43) |
| Single Ind | 0.47 | 0.06 | -0.04 | 0.47 | 0.07 | -0.04 |
| | (0.50) | (0.18) | (0.16) | (0.50) | (0.19) | (0.16) |
| Vertical integrate | -0.64** | 0.13 | 0.26*** | -0.67** | 0.11 | 0.27*** |
| | (0.37) | (0.15) | (0.13) | (0.38) | (0.15) | (0.13) |
| Total patent | 0.05 | 0.09* | 0.04 | 0.07 | 0.09* | 0.04 |
| | (0.15) | (0.06) | (0.06) | (0.15) | (0.06) | (0.06) |
| Prod patent | 0.69** | 0.04 | -0.23** | 0.58* | 0.03 | -0.20* |
| | (0.38) | (0.15) | (0.13) | (0.39) | (0.15) | (0.13) |
| BU size | 1.20*** | -0.21+ | -0.34*** | 1.16*** | -0.20 | -0.34*** |
| | (0.37) | (0.16) | (0.12) | (0.37) | (0.16) | (0.11) |
| Firm size | -0.87*** | -0.11 | 0.13 | -0.87*** | -0.13 | 0.13 |
| | (0.35) | (0.15) | (0.13) | (0.35) | (0.15) | (0.13) |
| Firm age | 0.02*** | 0.00 | 0.00 | 0.02*** | 0.00 | 0.00 |
| | (0.01) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | -32.51*** | 0.31 | -2.58 | -34.09*** | 0.71 | -2.41 |
| | (12.58) | (4.15) | (4.55) | (12.17) | (4.27) | (4.47) |
| Observations | 337 | 401 | 386 | 337 | 401 | 386 |
| R-squared | 0.26 | 0.18 | 0.16 | 0.27 | 0.19 | 0.16 |

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

**Table 15: Innovation performance for acquiring external innovation from startups vs other external sources (II)**

| VARIABLES | (1)<br>MSinc | (2)<br>%sale | (3)<br>%inno | (4)<br>MSinc | (5)<br>%sale | (6)<br>%inno |
|---|---|---|---|---|---|---|
| | Trademark | Trademark | Trademark | Proc Inno | Proc Inno | Proc Inno |
| Entrant | 2.23*** | 0.22 | -0.14 | 0.46 | -0.32 | -0.84+ |
| | (0.55) | (0.52) | (0.43) | (3.07) | (0.32) | (0.63) |
| CA discontinuity | -0.48 | -0.42*** | 0.06 | 0.53 | 0.19 | -0.05 |
| | (0.50) | (0.17) | (0.14) | (0.44) | (0.17) | (0.15) |
| CA*Ent | 1.55** | 0.40 | 0.14 | 2.53*** | 0.80*** | 0.10 |
| | (0.81) | (0.34) | (0.30) | (0.52) | (0.32) | (0.30) |
| Startup | 1.23*** | -0.05 | 0.00 | 1.19* | -0.28 | -0.11 |
| | (0.44) | (0.27) | (0.18) | (0.73) | (0.35) | (0.23) |
| Ent*Startup | -0.96+ | 1.61*** | 0.70* | 1.35 | 2.25*** | 1.30** |
| | (0.73) | (0.63) | (0.47) | (3.21) | (0.52) | (0.69) |
| CA*Startup | 0.39 | 0.50 | 0.54** | 0.32 | 0.65* | 0.40+ |
| | (0.74) | (0.48) | (0.32) | (0.85) | (0.43) | (0.30) |
| CA*Ent*Startup | 0.27 | 1.25*** | 0.44 | -0.09 | 1.61*** | 0.61* |
| | (1.11) | (0.46) | (0.37) | (1.08) | (0.51) | (0.39) |
| Single Ind | 0.47 | 0.09 | -0.02 | 0.46 | 0.08 | -0.06 |
| | (0.52) | (0.19) | (0.16) | (0.50) | (0.19) | (0.16) |
| Vertical integrate | -0.57* | 0.18 | 0.26*** | -0.60* | 0.13 | 0.23** |
| | (0.37) | (0.15) | (0.13) | (0.36) | (0.15) | (0.13) |
| Total patent | 0.04 | 0.10* | 0.03 | 0.06 | 0.06 | 0.05 |
| | (0.15) | (0.06) | (0.06) | (0.15) | (0.06) | (0.06) |
| Prod patent | 0.66** | 0.07 | -0.24** | 0.53+ | 0.01 | -0.23** |
| | (0.39) | (0.15) | (0.13) | (0.38) | (0.14) | (0.13) |
| BU size | 1.23*** | -0.16 | -0.34*** | 1.20*** | -0.22+ | -0.35*** |
| | (0.37) | (0.18) | (0.12) | (0.38) | (0.16) | (0.12) |
| Firm size | -0.78*** | -0.06 | 0.13 | -0.95*** | -0.11 | 0.13 |
| | (0.38) | (0.16) | (0.13) | (0.35) | (0.15) | (0.13) |
| Firm age | 0.02*** | 0.00 | 0.00 | 0.02*** | 0.00 | 0.00 |
| | (0.01) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | -34.34*** | 0.31 | -2.07 | -33.67*** | -1.02 | -2.10 |
| | (12.65) | (4.23) | (4.48) | (11.82) | (4.28) | (4.72) |
| | | | | | | |
| Observations | 337 | 401 | 386 | 336 | 398 | 383 |
| R-squared | 0.26 | 0.20 | 0.16 | 0.27 | 0.21 | 0.16 |

Standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

These evidences suggest that when firms are entering an industry and acquire external innovation from a startup, it is even more beneficial for them to modify their existing complementary assets to serve the newly acquired innovation product. Hypothesis 4 is supported.

### 3.4.5 Robustness checks

For robustness checks, we look at the subsample of firms that are standalone, as defined in Arora et al. (2016) and Bei (2019). Looking at standalone firms help us tease out the complications brought by the parent firms. But it also introduces further limitations for the firms' capabilities.

In Table 16, we show that within the subsample of standalone firms, they are more likely to implement changes in sales and distribution channels and changes in equipment and employee skills. There are no significant changes for filing new trademarks or process innovation. When we split the sample into new and old firms, we see that consistent with the whole sample analysis, new firms are significantly more likely to reconfigure their complementary assets across all four different types while the sample of old firms does not show any coefficient that is significantly positive.

**Table 16: Robustness checks on the subsample of standalone firms: likelihood of changing complementary assets**

| Sample | (1) Sale/Dist | (2) Equip/Skill | (3) Trademark | (4) Proc Inno |
|---|---|---|---|---|
| All firms | 0.26* | 0.38** | 0.20 | 0.20 |
| | (0.17) | (0.20) | (0.16) | (0.17) |
| Recent firms | 0.29* | 0.34* | 0.26** | 0.29* |
| | (0.19) | (0.22) | (0.16) | (0.18) |
| Old firms | -0.12 | 0.12 | -0.31 | -0.07 |
| | (0.52) | (0.51) | (0.39) | (0.34) |

In Table 17, we look at the innovation performance. We see positive coefficients for at least one of the innovation performance measure across three measures of complementary assets from the survey questions, with the only exception being filing for trademarks. It suggests that even for standalone firms, it is also beneficial for them to change their complementary assets to fit their external innovation better as they enter new industries. Similarly, we also see a benefit in implementing these changes in complementary assets when they source external innovation from startups, compared to from other sources.

The robustness checks are largely consistent with the main analysis and support our hypotheses.

**Table 17: Robustness checks on the subsample of standalone firms: innovation performance**

| Technology source | CA Type | (1) MSinc | (2) %sale | (3) %inno |
|---|---|---|---|---|
| All external | Sale/Dist | 5.01** | 1.27** | -0.11 |
| | | (2.71) | (0.72) | (0.62) |
| All external | Equip/Skill | 1.36 | 1.45* | 1.26** |
| | | (2.17) | (0.90) | (0.73) |
| All external | Trademark | -0.23 | 0.41 | -0.09 |
| | | (1.63) | (0.82) | (0.62) |
| All external | Proc Inno | 4.29** | -0.06 | 0.43 |
| | | (2.49) | (0.81) | (0.54) |
| Startups | Sale/Dist | -1.29+ | 0.73+ | -0.01 |
| | | (0.97) | (0.52) | (0.33) |
| Startups | Equip/Skill | -0.73 | 0.66+ | -0.22 |
| | | (1.09) | (0.48) | (0.38) |
| Startups | Trademark | 0.43 | 0.51 | -0.14 |
| | | (1.38) | (0.49) | (0.33) |
| Startups | Proc Inno | -0.40 | 1.17*** | 0.06 |
| | | (1.13) | (0.58) | (0.37) |

## 3.5 Conclusion and discussion

While the strategic management literature tells us a lot about firms' capability development before or during market entry (Helfat & Lieberman, 2002; Moeen, 2017), especially when they face technical discontinuities, much less effort has been spent on complementary asset discontinuities (Cozzolino & Rothaermel, 2018). In this study, we take an early step in understanding complementary asset discontinuities by looking at under what condition are firms more likely to change and reconfigure their existing complementary assets. Specifically, we look at firms' activities in changing four different types of complementary assets, sales and distribution channel, new equipment and employee skills, trademarks, and manufacturing process. And how are these changes correlated with firms' market entry and external technology sourcing activities?

Our findings are consistent with the Dynamic Capabilities (Teece & Pisano, 1994; Teece et al., 1997) framework in that, as firms are entering new industry context and adopting external technology in their innovation process, it is optimal for them to redeploy existing resources and capabilities to develop new complementary assets that fit better with the new industry and new product. We show that the more flexible firms in their routines (as newer firms), the more likely they will implement changes in their complementary assets as they enter a new industry and commercialize external innovation. Having changes in complementary assets also results in better innovation performance as firms enter a new industry and rely on external innovation. Furthermore, when the external innovation is sourced from a startup, it is even more beneficial for firms to be able to change their complementary assets, compared to external innovation obtained from other sources. This is potentially due to the higher appropriability that the acquiring firms main retain.

This study greatly benefits from the survey design from the Division of Innovative Labor survey (Arora, Cohen, et al., 2016). Their assessment of firms' changes in specific types of complementary assets enable us to create much more informative measures compared to the previous studies (Arora & Nandkumar, 2012; Helfat, 1997; Kapoor & Furr, 2015; Mitchell & Singh, 1992; Moeen, 2017; Rothaermel & Hill, 2005;

Tripsas, 1997). There are also several limitations imposed by this empirical setting. The survey is a cross-sectional data which does not allow to assess the long-run changes in complementary assets. Also, no causal claims are made in our empirical analysis as we are looking at correlations between changes in complementary assets, market entry, and external technology sourcing.

Despite these limitations, this study opens new revenues of future research and definitely calls for a deeper understanding of the role of complementary assets and the importance of reconfiguring existing complementary assets in the modern economy. Changes in complementary assets may not only affect firms' short-term profitability, but also the long term development of their technology (Wu, Wan, & Levinthal, 2014). With the emergence of platforms (Cozzolino & Rothaermel, 2018) and Artificial Intelligence technologies (Ajay Agrawal, Joshua Gans, & Avi Goldfarb, 2018) it is especially important to understand the changes in complementary assets that firms are facing and how to sustain their competitive advantage during this process.

# 4. Boundary Choices in Innovation: How does Availability of Hiring Affect Firms' Technology Sourcing Strategies

In this paper, I study the relationship between hiring and external technology sourcing. Hiring can either substitute for external technology sourcing by bringing new technologies/capabilities to a firm or complement external sourcing by providing information for evaluating and integrating external technology sources. The ability to transfer not only technologies but also technical capabilities further determines the differences in firms' external technology sourcing via the market for firms versus the market for technology. The empirical analysis employs a difference-in-differences causal inference design using staggered adoption of the inevitable disclosure doctrine (IDD), a state level law in the U.S. The results support the importance of hiring and demonstrate that when the external supply of technical labor is low, there is a substitution effect with external technology sourcing through the MFF but not the MFT. The substitution effect is more pronounced in states that have higher noncompete enforceability.

## *4.1 Introduction*

One of the fundamental questions for strategic management and technology innovation scholars is whether firms develop internally or externally to achieve the strategic renewal of capabilities and innovation (Agarwal & Helfat, 2009; Arora, Cohen, et al., 2016; West & Bogers, 2014). The existing literature has identified different modes that firms use to acquire technologies and capabilities and the factors that govern their selection of different modes (Arora, Cohen, et al., 2016; Capron & Mitchell, 2009; Mitchell & Shaver, 2003; Moeen & Agarwal, 2017). Although the literature on technology sourcing often treats internal innovation as the default option, there is a sharp distinction between innovation developed by existing employees (Tripsas, 1997) and innovation by newly hired inventors (Zucker & Darby, 1997), where hiring often provides the basis for more extensive innovation. However, the hiring option is not always available due to its reliance on external labor supply and legislative changes that affect this supply (Klasa, Ortiz-Molina, Serfling, & Srinivasan, 2017; Younge, Tong, & Fleming, 2015). However, we have only limited understanding of how the supply of technical labor via hiring affects firms' choices of other modes of external technology sourcing. In this study, I consider hiring to be an alternative to other modes of technology sourcing and study how the external supply of technical labor affects firms' external technology sourcing strategies.

Hiring new inventors brings firms both technical knowledge and technical capabilities for innovation, which could potentially be substituted by external technology sourcing. In addition, hiring is likely to complement external technology sourcing because it provides absorptive capacity (Cohen & Levinthal, 1990) and valuable insider information that lower the cost for target selection and integration. As external sourcing methods, the MFT and MFF differ in what opportunities they create for firms. The MFT, including licensing, patent right reassignment, or other types of transactions provides firms with new technology (Arora, Fosfuri, & Gambardella, 2001). By contrast, acquiring another company via the MFF provides a combination of technology and technical capabilities (Mitchell & Shaver, 2003). When the external supply of employees is constrained, firms can substitute this supply with either the MFF or the MFT to obtain codified technical knowledge, but they can only substitute it with MFF to obtain technical capabilities.

In the empirical analysis, I explore the relationship between the supply of external employees and firms' reliance upon the MFF and MFT to source external technology and capabilities. I employ a difference-in-differences causal inference design, based on staggered adoption of the inevitable disclosure doctrine (IDD). The IDD is a legal doctrine to protect firms' trade secret by preventing its employees from moving to competitor firms, by different states in the US to identify exogenous changes in the supply of employees (Klasa et al. 2014).

The findings suggest a substitution effect between hiring external employees and external technology sourcing through the MFF, but not the MFT. This is potentially due to the differences in their ability to source tacit technical capabilities and human capital. When the state level noncompete enforceability is high, the substitution effect is stronger compared to states with lower noncompete enforceability – which further supports the key argument that it is the ability of hiring new inventors from externally, rather than the implementation of IDD itself, that leads to the firms' substitution with external technology sourcing.

These findings advance our understanding of strategic resource development (Capron & Mitchell, 2009) and technology-sourcing strategies (Arora, Cohen, et al., 2016) by linking employee mobility (Mawdsley & Somaya, 2016) to external technology sourcing. Drawing upon the Build-Borrow-Buy framework (Capron & Mitchell, 2012), this study takes the new angle to distinguish between internal development carried out by new hires versus existing employees and shows how the ability to hire new employees affects firms' technology sourcing strategies. It is the first effort to match both patent filings and patent assignment data to the universe of U.S. manufacturing sectors while distinguishing between patents obtained through different channels.

The remainder of this paper is organized as follows: Section Two describes the theoretical background and hypothesis development; Section Three introduces the data generation process, the difference-in-difference framework, and the estimation methodology; Section Four presents the results; and Section Five provides a summary of the findings and a brief discussion.

## *4.2 Theoretical Framework*

### 4.2.1 Modes of technology sourcing

The existing literature on resource-based perspectives, dynamic capabilities, and strategic renewal suggests that firms commonly use a combination of different modes to renew their capabilities and maintain their competitive advantage (Agarwal & Helfat, 2009; Helfat et al., 2007). Firms use internal development to exploit existing resources and capabilities and use external sourcing to obtain new capabilities – which also help firms overcome obsolescence and inertia (Helfat, 1994, Rosenkopf & Nerkar, 2001; Vermeulen & Barkema, 2001). The choice that firms make regarding which mode they will use to develop new resources and renew their capabilities – internally or externally, through service contracts, alliances, or acquisition – is critical. A study of selective capabilities (Capron & Mitchell, 2009) reported that the choice of mode is dependent on a firm's capability gaps and internal social institutions. Lee and Lieberman (2010) demonstrated that the choice is also related to the distance of the new market from the firm's primary business domain.

The literature on the economics of innovation and technology management has also identified that firms use a variety of modes of technology sourcing and knowledge development, especially during periods of market creation and competence-destroying technological change. This phenomenon is largely captured in studies on open innovation (West & Bogers, 2014) and the division of innovative labor (Arora, Cohen, et al., 2016; Arora & Gambardella, 1994b; Arora & Merges, 2004). For internal development, firms can either rely on existing inventors (Tripsas, 1997) or hire new human capital (Zucker & Darby, 1997). For external sourcing, firms can obtain technology through the MFT (Arora et al., 2001) or the MFF (Higgins & Rodriguez, 2006;

Mitchell & Shaver, 2003) or by forming strategic alliances (Rothaermel, 2001). Arora et al. (2016) demonstrated that approximately half of their survey respondents that generated new-to-the-market innovation indicated having used external technology sources for their innovation. The prevalence of combining internal and external sources of innovation has also been identified in other studies (Kapoor & Klueter, 2015; Moeen & Agarwal, 2017; Rothaermel & Thursby, 2007).

The above two streams of literature have different views regarding internal capability development. In the strategic management literature, internal development is path dependent (Cohen & Levinthal, 1990; Kraatz & Zajac, 2001; Penrose, 1959) and exploitive (Helfat, 1994; Stuart & Podolny, 1996). External sourcing enables firms to search distantly, overcome the inertia pressure associated with an internal search (Rosenkopf & Almeida, 2003), and reach beyond a larger capability gap (Capron & Mitchell, 2009). According to the technology innovation literature, it is possible to adopt new technologies and to obtain technical capabilities by hiring new inventors during periods of technological change (Zucker & Darby, 1997). However, scholars have rarely distinguished between internal innovations developed by existing inventors versus those developed by newly hired inventors (e.g., Arora et al., 2016; Cassiman & Veugelers, 2006). In parallel, we do not have a comprehensive understanding of the importance and strategic value of hiring in helping firms to gain new technology.

### 4.2.2 Importance of hiring during new technology development

Strategy and technology management scholars have devoted a great deal of effort to document and explain the inability of incumbent firms to adapt to technology changes (Christensen, 1997; Henderson & Clark, 1990; Tripsas, 1997; Tripsas & Gavetti, 2000; Tushman & Anderson, 1986). One common challenge faced by incumbent firms is that they suffer from inertia in their technology bases, organizational routines, investment strategies or consumer bases (Hill & Rothaermel, 2003). Such organizational inertia imposes a real burden on firms during technological change – which often requires changes in operating procedures and even the underlying knowledge base.

One way in which firms sustain through technological changes is by developing new skills, which can be achieved either by educating existing employees or by hiring new employees with new skills (Tripsas, 1997; Zucker & Darby, 1997). Two prominent examples of technological changes are nanotechnology and biotechnology (Rothaermel & Thursby, 2007). Based on a sample of U.S. manufacturing firms adopting nanotechnology or RNAi (RNA interference, a novel technique in biotechnology), firms that innovate using these new technologies are likely to have new inventors who joined the firm later to work on these new technologies compared to the firm's average set of inventors. If a firm's initial mode of adopting the new technology is through an external source, then its internal development is likely carried out by inventors who joined the firm even later. Additionally, based on inventor-firm matched data, an inventor's average patent life associated with a firm is approximately six to seven years (Table 18) – which is true for both average firms and the subset of firms that adopted nanotechnology or RNAi.

**Table 18: Inventor's patent life within a company (year)**

| Sample | All | NANO | RNAI |
|---|---|---|---|
| mean | 6.89 | 6.01 | 6.37 |
| SD | 7.16 | 6.03 | 6 |
| median | 5 | 5 | 5 |
| 95 pctile | 22 | 19 | 17 |

Note:
This is a summary statistic for the inventor's patent life (year) within a company.
Patent life is measured by the number of years between when the inventor had the first patent and the last patent with a company, dated by the year of initial filing.
Column 1 is the summary statistics for all sample. Column 2 is for firms that have at least one patent on Nanotechnology. Column 3 is for firms that have at least one patent on RNAi.

These lines of evidence from the prior literature and from examples of technological changes suggest that hiring is important for firms' innovation activity. In particular, as firms attempt to develop new technologies, hiring can help them to obtain the necessary technical capability and knowledge to achieve this goal. The specific feature of hiring in developing new technology suggests that it might be an alternative to other modes of external technology-sourcing strategies such as the MFF, the MFT, and alliances. In this study, I study the relationship between the external supply of technical labor and external technology-sourcing activities, focusing on the MFF and the MFT.

### 4.2.3 Hiring and external technology sourcing: substitutes or complements?

The employee mobility literature frequently discusses organizational outcomes of the inter-organizational movement of personnel. Employee movement brings benefits to the receiving firms in innovation (Rao & Drazin, 2002; Song, Almeida, & Wu, 2003), including learning (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011), capability acquisition and divestiture (Agarwal, Echambadi, Franco, & Sarkar, 2004). Employee mobility transfers both human capital and relational capital, which means that the receiving firms obtain new skills, knowledge, or relationships, whereas the losing firms either lose valuable assets or benefit from new relational capital (Mawdsley & Somaya, 2016). One of the most prominent benefits of employee mobility arises for innovation and spillovers of technological knowledge, where different types of valuable assets are transferred during the process. These valuable assets include tacit knowledge that underlies the technologies invented by the source firm (Tzabbar, Aharonson, & Amburgey, 2013), key routines that help recipient firms develop new technology trajectories (Song et al., 2003; Tzabbar, 2009), and external information networks that help enhance absorptive capacity (Cohen & Levinthal, 1990). The benefit for the recipient firms' subsequent innovation has been documented by patent citation patterns (Rosenkopf & Almeida, 2003; Song et al., 2003).

By default, employees are free to quit their employers (Coff, 1997), and firms can hire whoever they want. However, various constraining factors impede this process –

and here I focus on supply-side factors. The total supply of human capital that has the necessary knowledge and skills is one important concern for the supply of labor. This is also true for the early stage of technological changes when there are not many skilled labors in the labor market. In addition, valuable human capital may already be involved with other companies and are not willing to move. Even if they do, there are many policy or legislative procedures that restrict their ability to move, such as the non-compete clauses or the Inevitable Disclosure Doctrine (Klasa et al., 2017; Younge et al., 2015). Thus, firms may frequently face the problem of efficiently sourcing human capital due to supply-side constraints.

When employee mobility is compromised, firms can use alternative routes to benefit without hiring new talent, including network and geographic knowledge spillovers, acquisitions, and alliances (Mawdsley & Somaya, 2016). For example, acquisition has long been recognized as a viable mechanism for interfirm learning, knowledge transfer, and capability reconfiguration (Ahuja & Katila, 2001; Karim & Mitchell, 2000; Song et al., 2003; Younge et al., 2015). Recent developments in this literature have also investigated the new phenomenon of "acqhires" (Chatterji & Patro, 2014; Coyle & Polsky, 2013). Similarly, strategic alliances bring firms opportunities to exchange knowledge and resources; representing an alternative to bringing in new employees (Hamel, 1991; Inkpen, 1998; Kale & Singh, 2007).

Connecting the employee mobility literature to the technology-sourcing context, the employee mobility literature implies that hiring new inventors is potentially a substitute to other modes of technology sourcing – although the innovation output that we actually observe is in the form of an internal patent. Consequently, when inventor mobility is constrained, in order to access new technology, firms may pursue external technology sourcing as a substitute.

*H1. (Substitution) The lower the supply of external employees, the more likely that firms will obtain technology from external sources.*

Now consider an alternative argument to H1. The literature examining the relationship between internal and external sources of technology sourcing has suggested internal knowledge sourcing and external knowledge sourcing complement one another (Cassiman & Veugelers, 2006; Love, Roper, & Vahter, 2014). There are different factors that condition the level of complementarity (Grigoriou & Rothaermel, 2017), including absorptive capacity (Cohen & Levinthal, 1990), intellectual property, the type of research and development conducted (Cassiman & Veugelers, 2006), the types of experience in different learning stages (Hoang & Rothaermel, 2010), and internal knowledge network properties (Grigoriou & Rothaermel, 2017). This literature suggests that, due to the high uncertainty and risk in conducting and contracting for innovation, the sourcing firm requires the ability to properly evaluate external technology during the external sourcing process (Cohen & Levinthal, 1990). Newly hired inventors contribute to the firms' internal innovation workforce and technical capabilities; they are a valuable source of the firms' absorptive capacity that potentially facilitate the firms' external technology-sourcing activities to help them understand and evaluate external technology.

In addition, external employees have valuable insider information about their original employers – either a potential target for the MFF or a potential supplier for the MFT. This valuable insider information can be important for resolving the information asymmetry problem (Akerlof, 1970; Ragozzino & Reuer, 2011) during technology sourcing and lower the cost for subsequent integration. As a result, firms are likely to choose their targets for external technology sourcing from among firms that have previous ties with their hired employees. Thus, when inventor mobility is constrained, firms are likely to perform less external technology sourcing.

*H2 (alternative to H1). (Complement) The lower the supply of external employees, the less likely that firms will obtain technology from external sources.*

In this study, I consider two different types of external technology sourcing, the MFF, and the MFT, and test on the hypotheses separately.

### 4.2.4 Additional notes on the differences between the market for firms and the market for technology

There is a whole spectrum of choices that firms may pursue during external sourcing, ranging from the more integrated approach such as the parent-subsidiary relationship to pure arm's length market transaction (Rothaermel, 2018). Lying in the middle of this make-or-buy continuum are different types of strategic alliances, including short-term contracts, licensing, franchising, equity alliances, and joint ventures. For ease of analysis and interpretation, in this study, I focus on the two extremes on the make-or-buy continuum: the market for firms, and the market for technology represented by the full reassignment of property right.

The different modes of external technology sourcing vary in the content delivered. There are two types of technological knowledge: codified technical knowledge and tacit technical capabilities (Nelson & Winter, 1982; Winter, 1987). The MFT transfers codified technical knowledge through arms-length transactions, which are largely promoted with efficient patent protection (Arora & Ceccagnoli, 2006). However, it is harder to transfer tacit technical capabilities through the MFT (Arora & Gambardella, 1994b; Kogut & Zander, 1992; von Hippel, 1990; Winter, 1987). On the other hand, the resourced-based view considers the firm to be a bundle of resources and assets (J. B. Barney, 1986; Wernerfelt, 1984), and the resource base can be changed or modified through its dynamic capability (Helfat et al., 2007). By acquisition, firms can obtain important resources and capabilities to achieve further growth (Capron, Dussauge, & Mitchell, 1998). This point is especially true for technological acquisitions in which an acquirer obtains access to the target firm's knowledge base and technological capabilities (Ahuja & Katila, 2001). Acquisition enables the firm to access the target firm's specific know-how (O. Bertrand, 2009) and is more appropriate than other modes of technology sourcing when the underlying knowledge is tacit (Ranft & Lord, 2002). Thus, technology sourcing through the MFF grants the acquiring firm both codified technical knowledge and tacit technical capabilities associated with the target firm.

When firms have difficulty hiring new inventors, they are lack of both new technical knowledge and the tacit technical capabilities. Even though both the MFT and the MFF can provide new technical knowledge, only the MFF is able to provide the underlying tacit technical capabilities. Thus it is expected that firms' response in external technology sourcing through the MFF and the MFT would be different under this condition – namely, the MFF may be more responsive to a constraint in hiring new inventors.

## 4.3 Data and Methods

### 4.3.1 Sample

The sample for this study is drawn from the 2013 National Establishment Time Series (NETS) database. The NETS database is developed by Walls & Associates by combining the Dun and Bradstreet (D&B) archival establishment data into a time-series database that contains establishment level information in the US. A snapshot of the D&B data is taken every January from the full Dun Marking Information file, and no establishments are deleted from the database. Even though the NETS database has not been used widely in the strategic management literature, it is based on the same source data (D&B) data for the Bureau van Dijk Orbis Database prior to 2013. And the Orbis database has been used in the strategic management literature (Arora, Belenzon, & Rios, 2014). Thus, the NETS database is a comprehensive database that provides annual records for a large part of the US economy. It provides easy access to track the changes in each establishment across different years. Especially, it provides ownership information (similar to Orbis) and ownership changes that help identify establishment level acquisition.

Each firm is defined as an active headquarter firm recorded in 2010, from which I draw information on its M&A activities and other information. The 2010 headquarter firms are further grouped if the firms had the same firm name – representing the same firm under the same larger corporate group. The grouping of firms follows a similar procedure as the patent matching process (see Appendix II for further details), which is based on firm name string matching. If two firms have the same name, then the matching process did not distinguish between the two. Because this study focuses on U.S. manufacturing firms, universities and banks are eliminated from the sample by a word search of "UNIV," "COLLEGE," or "BANK." These institutions are eliminated because universities have a different patenting strategy from industrial companies (Trajtenberg, Henderson, & Jaffe, 1997), whereas banks have numerous patent assignment activities as collateral (Marco, Myers, Graham, Agostino, & Apple, 2015), both of which are irrelevant to this analysis.

As described in the Appendix II, the firms are linked to the United States Patent and Trademark Office (USPTO) patent and patent assignment data by firm name string matching. In addition, patents are categorized as internal patents (developed internally and having the original firm as the assignee), MFT patents (developed by another party and reassigned to the firm), or MFF patents (obtained through M&A). The year for internal patents is defined as the year of filing. The year for MFF or MFT patents is defined as the year that the acquisition or deal is made. See Figure 2 for the aggregate year trend for each of the patent types. This matched dataset is linked to the Harvard Patent Inventor Dataverse (Li et al., 2014), which provides further information on inventors and their locations.

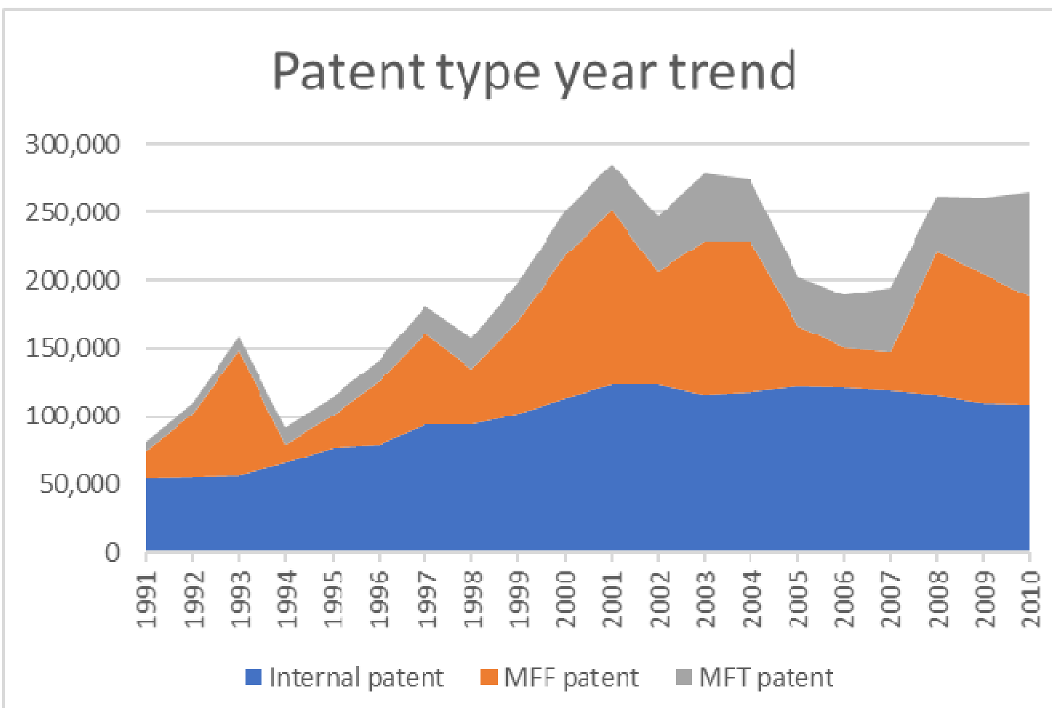


**Figure 2: Aggregate annual patenting activity by different types of patents**

Because the IDD treatment in this study is at the state level, the resulting treatment effect is also assessed within the boundaries of a state. I further assign patents to individual establishments based on the minimum distance between the patent inventor and the establishment. The sample is further eliminated to focus on patents that are at the same state as the matched firm establishment.

The time frame for the sample is from 1991 to 2010. I only look at headquarter firms that are active throughout the whole time period to eliminate the unexpected effect of firm entry and exit on the measurement of external technology sourcing. That way, this study focuses on a relatively stable sample of firms and looks at their firm-level strategy in patenting, acquisition, and their involvement in the market for technology. A firm is included only if there is at least one patent (that could be from any of the three types of patent) matched to the firm during the matching process.

The empirical analysis is at the firm-state-year level. Because a firm can operate in different states at different time, they do not necessarily have any patenting or external technology sourcing activity in that state during a certain time period. So for each firm-state, its "real active period" is defined as from the year it has its first matched patent until the year it has its last matched patent. If no patent is matched for years between the first and last year, the firm-state-year is still included as an observation, and the number of patents is set to zero for all three types of patents. For time periods that are outside this "real active period", the observations are excluded from the final sample.

The final sample consists of 16,464 firms, and 206,400 firm-state-year observations. See Table 19 for the summary statistics and correlation matrix.

**Table 19: Summary statistics and correlation matrix**

| | Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| (1) | MFF Patents | 206,400 | 2.76 | 53.31 | 0 | 11750 |
| (2) | MFT Patents | 206,400 | 0.94 | 22.24 | 0 | 6119 |
| (3) | Treatment (IDD) | 206,400 | 0.51 | 0.50 | 0 | 1 |
| (4) | Enforceability | 206,400 | 0.46 | 0.50 | 0 | 1 |
| (5) | Internal patents | 206,400 | 2.63 | 21.02 | 0 | 2255 |
| (6) | Sales (log) | 206,400 | 18.79 | 3.96 | 0 | 25.39 |
| (7) | Employment (log) | 206,400 | 7.24 | 2.98 | 0 | 13.88 |
| (8) | Noncompete Index | 206,400 | 4.07 | 2.09 | 0 | 9 |
| (9) | Firm age | 206,400 | 66.63 | 43.03 | 21 | 410 |
| (10) | Firm total internal patent (log) | 206,400 | 1772.07 | 5054.79 | 0 | 43818 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.00 | | | | | | | | | |
| (2) | 0.01 | 1.00 | | | | | | | | |
| (3) | 0.00 | 0.00 | 1.00 | | | | | | | |
| (4) | 0.00 | 0.00 | 0.15 | 1.00 | | | | | | |
| (5) | 0.01 | 0.03 | 0.00 | -0.01 | 1.00 | | | | | |
| (6) | 0.04 | 0.03 | 0.00 | 0.06 | 0.05 | 1.00 | | | | |
| (7) | 0.05 | 0.03 | -0.01 | 0.06 | 0.06 | 0.92 | 1.00 | | | |
| (8) | -0.01 | -0.01 | 0.38 | 0.45 | -0.03 | 0.08 | 0.09 | 1.00 | | |
| (9) | 0.02 | 0.03 | 0.01 | 0.05 | 0.02 | 0.37 | 0.46 | 0.10 | 1.00 | |
| (10) | 0.01 | 0.02 | -0.02 | 0.03 | 0.19 | 0.27 | 0.34 | 0.03 | 0.17 | 1.00 |

### 4.3.2 Dependent variables

*Number of MFF patents:* The total number of MFF patents (obtained through M&A) is generated at the firm-state-year level, representing the level of external technology-sourcing activities through the MFF within the state each year. The variable is log-transformed to approximate a normal distribution.

*Number of MFT patents:* The total number of MFT patents (obtained through the market for technology) is generated at the firm-state-year level, representing the level of external technology-sourcing activities through the MFT within the state each year. The variable is log-transformed to approximate a normal distribution.

### 4.3.3 Independent variables

*IDD (treatment variable)*: IDD is an indicator variable that equals one if the state had the IDD in place that year. The information for the state adoption and rejection of the IDD was based on Klasa et al., (2017). See the next section for a discussion on the validity of using the IDD as the treatment.

*Enforceability*: In the last analysis, I also look at heterogeneous treatment effects by categorizing the sample into high and low noncompete enforceability based on Starr (2019).

### 4.3.4 Control variables

Whenever applicable, firm age is calculated based on the year of establishment for the headquarter firms. Firm total patenting is calculated based on the internal patents of the matched patent sample. Firm sales and total employees are calculated each year and are thus controlled as a firm-level time-varying variable.

At the state level, following Flammer and Kacperczyk (2017), I include the noncompete index developed by Garmaise (2009) to control for the enforcement of noncompete clauses in the state.

See Table 20 for analysis based on different model specifications. The main analysis uses firm fixed effect, state fixed effect, and year fixed effect throughout this study. Robust standard errors are clustered at the state level throughout the analysis.

**Table 20: Treatment effect based on different model specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Dep var=log(# of MFF patents) | | | Dep var=log(# of MFT patents) | | |
| IDD | 0.03*** | 0.05*** | 0.01+ | 0.01+ | 0.03*** | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) |
| Internal patent | -0.06*** | 0.00 | -0.01 | 0.09*** | 0.10*** | 0.09*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Sales | -0.01*** | -0.01*** | -0.01*** | -0.01*** | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Employment | 0.07*** | 0.06*** | 0.06*** | 0.03*** | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Firm age | -0.00*** | | | 0.00*** | | |
| | (0.00) | | | (0.00) | | |
| Noncompete Index | -0.01*** | -0.02** | -0.01 | -0.01*** | -0.02** | 0.01* |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) | (0.00) |
| Constant | 0.17*** | 0.10*** | -0.17*** | 0.05*** | 0.11*** | -0.10*** |
| | (0.01) | (0.02) | (0.05) | (0.01) | (0.02) | (0.03) |
| Observations | 206,400 | 206,400 | 206,400 | 206,400 | 206,400 | 206,400 |
| R-squared | 0.07 | 0.21 | 0.22 | 0.05 | 0.25 | 0.26 |
| Year FE | YES | YES | YES | YES | YES | YES |
| Firm FE | NO | YES | YES | NO | YES | YES |
| State FE | NO | NO | YES | NO | NO | YES |
| VCE cluster | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$

Note: This table shows the firm-state-year level assessment of the treatment effect of IDD, based on different model specifications. Columns 1 through 3 look at the MFF patents, and columns 4 through 6 look at the MFT patents. All models control for internal patenting, firm level time-variant variables such as sales and employment, the state level non-compete index, and firm age when firm fixed effect is not applied. Robust standard errors are clustered at the state level. Columns 1 and 4 include year fixed effect. Columns 2 and 5 include year and firm fixed effect. Columns 3 and 6 include year, state, and firm fixed effect. In the subsequent analysis, the last model is selected (columns 3 and 6).

## 4.3.5 Inevitable disclosure doctrine (IDD)

The IDD is a legal doctrine that protects a firm's trade secrets by eliminating employees' ability to work for a direct competitor of the firm. The IDD is applicable based on "threatened misappropriation," which suggests that as long as there is a threatened disclosure of the firm's trade secrets, the firm may ask state courts to prevent its employees from working for a competitor in similar positions. It applies to the state of an employee's original firm even if the potential new employer is in another state without the IDD (Garmaise, 2011; Klasa et al., 2017).

### 3.3.5.1 Difference-in-differences design

This study examines the state adoption of the IDD as the exogenous source of variation to study firms' technology sourcing behavior when employee mobility is low. A difference-in-difference methodology was utilized based on the 21 treatments listed in Klasa et al. (2017). For those states, a precedent-setting case became case law and represented the start date of the state court recognizing the IDD. For three of the states, IDD recognition was later reversed in a subsequent court decision. The IDD indicator equals one if the state court recognizes the IDD in the year and zero otherwise. For the other 29 states that never explicitly considered or rejected the IDD, the IDD indicator is equal to zero in every year. This study followed Bertrand and Mullainathan's (2003) methodology in the presence of staggered treatments at the state level and estimated the following regression:

$$Dep\ Var_{ist} = \alpha_i + \alpha_s + \alpha_t + \beta_E IDD_{st} + \gamma' X_{ist} + \varepsilon_{ist}$$

where $i, s,$ and $t$ index firms, the state, and the year, respectively; $\alpha_i$, $\alpha_s$, $\alpha_t$, represent firm, state, year fixed effects, respectively. $\varepsilon$ is the error term. Because the analysis at the level of external technology sourcing is based on count variables, I use Ordinary Least Square (OLS) with log-transformed count variables to estimate the coefficients. The coefficient of interest is $\beta_E$, which measures the effect of the IDD on the amount of externally sourced technology.

**4.3.5.2 The validity of the identification strategy**

To satisfy the relevance condition, the adoption of the IDD must result in changes in the level of employee mobility. Klasa et al. (2017) used the Census Bureau's Survey of Income and Program Participation to show that the recognition of the IDD significantly reduced the mobility of knowledge workers in possession of the firm's trade secrets. Studies have also shown that rejection of the IDD was correlated with an increase in the knowledge of workers' mobility (Png & Samila, 2015). These studies supported the relevance condition that with the presence of the IDD, employee mobility is lower; without the IDD, employee mobility is higher.

Further discussion on the validity of the treatment using IDD follows Athey and Imbens (2018). For the design assumption, the assignment of the treatment needs to be random, conditional on the potential outcomes and possibly pretreatment variables. In the data, there is no strong correlation between the state level IDD assignment and the innovation activities, including internal patenting and external patenting of the firms.

For the exclusion restriction, the identification strategy assumes that the adoption of the IDD was exogenous regarding firms' innovation and technology-sourcing strategies. I now discuss why this assumption is likely to be valid. The adoption of the IDD at the state level is not based on state laws that could be influenced by lobbying. Instead, it is based on specific precedent-setting cases driven by the merits of the involved companies and the final judicial decision. Because of the potential significant harm to a firm upon the loss of trade secrets, state courts often make decisions on precedent-setting cases quickly, which makes it difficult for the average firm to anticipate this change ex-ante. The main purpose of judicial decisions involving the IDD is to balance employers' interests in protecting trade secrets and the public policy concern regarding employee mobility and freedom of employment (Godfrey, 2004; Harris, 2000), and it is less likely to be affected by individual firms' technology-sourcing strategy. When IDD is adopted, all firms in the state are exposed to the restriction imposed by IDD, and it does not matter how long the adoption has happened. Thus satisfies the second assumption by Athey and Imbens (2018).

The staggered treatment allowed the eventually treated firms to be in the control group first and in the treatment group later. This treatment also allowed me to run the regression analysis using only the eventually treated firms – which is consistent with the main analysis and the hypotheses.

### 4.3.6 Alternative analysis based on matched sample

The identifying assumption in the difference-in-difference design is that, without the IDD, the average technology-sourcing activity in the treated and control groups follows a parallel trend before and after the IDD. This issue raises a concern about the comparability of the control and treated states as a whole and calls for the importance of matching firms in the treatment group with appropriate counterparts in the control group while executing the difference-in-difference research design. Thus, I further utilize the propensity score matching (PSM) methodology to create relatively balanced treatment and control groups to estimate the treatment effect.

PSM is the most common "clone-finding" method, (Hirano, Imbens, & Ridder, 2003; Imbens & Rubin, 2015). The estimation of the propensity score is based on firm characteristics including year of establishment, total internal patenting, current year sales and employment, and state status for other noncompete clauses. The estimation equation controls for the same set of covariants. The final estimation model uses inversed propensity weighting.

## 4.4 Results

### 4.4.1 Baseline analysis at the state-year level

The logic underlying my argument is that firms have incentives to hire new inventors to innovate using new technologies during technological changes (Tripsas, 1997; Zucker & Darby, 1997), yet sometimes face constraints on their ability to hire. Drawing on the literature on employee mobility and technology sourcing, I develop competing hypotheses concerning whether constraints on hiring lead to greater or lesser external sourcing, depending on whether hiring new inventors and pursuing external technology sourcing are substitutes or complements. To test which of the complementary or substitution forces dominates, this study employs a difference-in-difference design utilizing the stepwise state adoption of the IDD to investigate the impact of employee mobility on firms' external technology sourcing. Specifically, I examine two different modes of technology sourcing: patents obtained through the MFF; and patents obtained through the MFT.

In the first step, I look at the aggregate changes in external technology sourcing in response to the IDD treatment at the state level. Figure 3 illustrates the average number of patents transferred through the MFF or the MFT at the state level in each year. Here I am only showing the states that eventually received the IDD treatment at some point, and all states are aligned to the year of initial IDD adoption. At the aggregate level, we can see that the number of patents transferred through the MFF or

MFT is higher after the IDD treatment. The average level of MFF patent seems to be increasing several years before the treatment, but stays the same in the year before the treatment. The average level of MFT patent seems to be flat and does not have much change before the treatment.

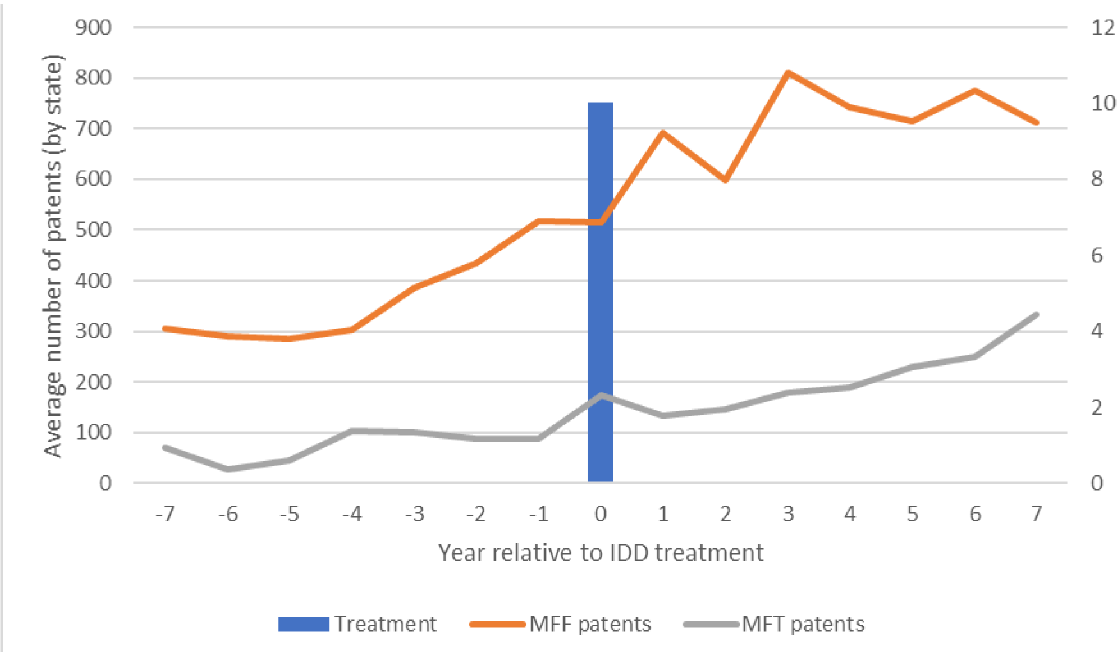


**Figure 3: Technology sourcing time trend (by patent count) for treated states**

Note:
This figure shows the pre- and post-treatment trend of external technology sourcing (by total patent count) in states that received the treatment in the upper panel. 0 means the year the IDD treatment was adopted. All states that received treatment are aligned relative to the year of treatment; then the aggregate patent count is calculated and shown here

Additional evidence is also available based on the patent licensing records from the KtMine data. See Figure 4 for a comparison of the number of licensed patents with and without IDD treatment.

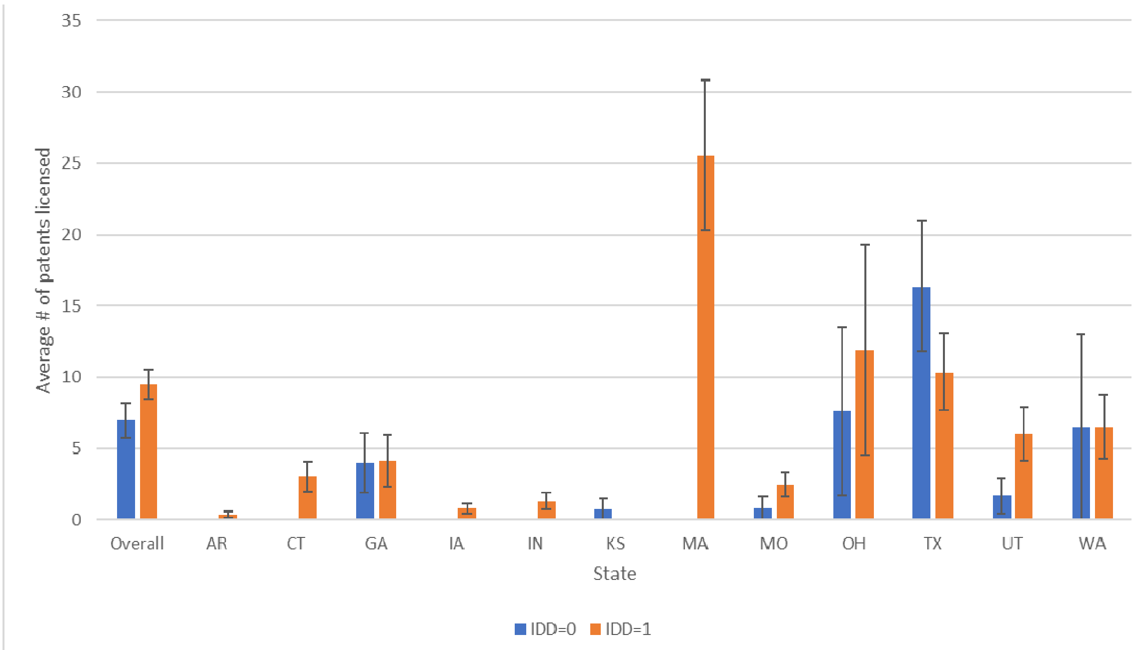


**Figure 4: Compare the level of patent licensing before vs after the IDD treatment**

Note:
This figure compares the pre- and post-treatment level external technology sourcing overall, and in states that received the treatment in middle of the sample period. Different from the main regression analysis, this figure is based on the KtMine data which documents licensing agreements. For each state shown above, the left bar shows the average number of patents transferred through licensing in the years that the state does not adopt IDD, and the right bar shows the average number of patents transferred through licensing in the years that the state adopts IDD.

Table 21 shows the regression analysis at the state-year level after controlling for the state level internal patenting and the state fixed effect. Robust standard errors are clustered at the state level. Columns (1) and (2) look at technology sourcing through the

MFF, and Columns (3) and (4) look at technology sourcing through the MFT. Based on this analysis, there is a significant increase in patent transferred through both the MFF and the MFT upon the treatment of IDD. There is about a 25 percent increase of the MFF patent, and a 57 percent increase of the MFT patent at the state level.

**Table 21: Treatment effect on external technology sourcing at the state-year level**

| VARIABLES | (1)<br>MFF | (2)<br>MFF | (3)<br>MFT | (4)<br>MFT |
|---|---|---|---|---|
| IDD | | 0.25** | | 0.57*** |
| | | (0.14) | | (0.28) |
| Internal patent | 0.01 | 0.01 | -0.05* | -0.05+ |
| | (0.02) | (0.02) | (0.03) | (0.03) |
| Constant | 1.52*** | 1.52*** | 0.45*** | 0.45*** |
| | (0.04) | (0.04) | (0.06) | (0.06) |
| Observations | 999 | 999 | 999 | 999 |
| R-squared | 0.77 | 0.77 | 0.79 | 0.80 |
| State FE | YES | YES | YES | YES |
| VCE cluster | YES | YES | YES | YES |

Robust standard errors in parentheses
*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$
Note: The analyses in this table are performed at the state-year level. The dependent variable Are the aggregated number of patents transferred through the MFF (1 and 2) and the MFT (3 and 4) in each state-year, respectively. The models control for state-year level internal Patenting, state fixed effect and the robust standard errors are clustered at the state level. It Shows a positive treatment effect on both MFF and MFT patents.

### 4.4.2 Treatment effect on external technology sourcing at the firm-state-year level

In order to understand the firm-level changes in technology sourcing strategy, in the next step, the analysis of the treatment effect of IDD on external technology sourcing is assessed at the firm-state-year level. Table 22 shows regression analysis at the firm-state-year level, with dependent variables measuring the count of patents obtained through the MFF (columns 1 to 3) or the MFT (columns 4 to 6). This model includes year fixed effect, state fixed effect, firm fixed effect, and several time-variant firm-level variables. It also includes the non-compete index to control for the state level non-compete implementation.

**Table 22: Treatment effect on external technology sourcing at the firm-state-year level**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Dep var=log(# of MFF patents) | | | Dep var=log(# of MFT patents) | | |
| | All | All | Treated | All | All | Treated |
| IDD | | 0.01+ | 0.01+ | | -0.00 | -0.00 |
| | | (0.00) | (0.00) | | (0.00) | (0.00) |
| Internal patent | -0.01 | -0.01 | -0.01* | 0.09*** | 0.09*** | 0.09*** |
| | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) | (0.01) |
| Sales | -0.01*** | -0.01*** | -0.01*** | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Employment | 0.06*** | 0.06*** | 0.06*** | 0.00 | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Noncompete Index | -0.01+ | -0.01 | -0.00 | 0.01* | 0.01* | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -0.17*** | -0.17*** | -0.13*** | -0.10*** | -0.10*** | -0.13*** |
| | (0.05) | (0.05) | (0.03) | (0.03) | (0.03) | (0.03) |
| Observations | 206,400 | 206,400 | 131,943 | 206,400 | 206,400 | 131,943 |
| R-squared | 0.22 | 0.22 | 0.23 | 0.26 | 0.26 | 0.28 |
| Year FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| State FE | YES | YES | YES | YES | YES | YES |
| VCE cluster | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20
Note: This table shows the firm-state-year level assessment of the treatment effect of IDD using the selected full model. Columns 1 to 3 look at the MFF, and columns 4 to 6 look at the MFT. Columns 1 and 4 include only controls and columns 2 and 5 also include the treatment variable IDD. Columns 3 and 6 are based on the sample of states that eventually received the treatment. The result suggests there is a 1 percent increase on MFF patents upon IDD treatment, indicating a strong substitution effect. Based on the results, there is no substitution effect for the MFT patents.

From this analysis, we can see that upon the IDD treatment, there is on average a 1 percent increase in the amount of MFF patent. It suggests that firms are more likely to acquire other companies to obtain technology when facing constraint in hiring new inventors. As discussed in the theory section, this can be explained by firms' incentive to obtain new technology from externally when hiring is not easy, and also reflects the fact that firms acquire other companies to obtain their human capital and technical capabilities. For the MFT patents, there is not a significant treatment effect on either substitution or complementarity. This is potentially due to the need to obtain technical capabilities, that firms are not able to achieve through the MFT. The treatment effect also holds when the analysis is performed based on the sample of the states that eventually received the treatment (columns 3 and 6).

In conclusion, the main analysis suggests there is a substitution effect for the MFF, but not for the MFT.

### 4.4.3 Heterogeneous treatment effect based on state noncompete enforceability

The IDD is essentially one special type of noncompete clauses. Unlike most of the other non-compete clauses that are written in the employment contract, the IDD is not written in a contract and is applicable as long as there is threatened disclosure of the firms' trade secrets. Yet the IDD essentially provides an option to sue potential moving employees, and its enforceability is largely based on the employer's willingness to pursue a lawsuit. Thus the state level noncompete enforceability is relevant here because it is correlated with how difficult it is to hire new inventors when IDD is present. When IDD is adopted in a state, if the noncompete enforceability is high, then firms in the state are more likely to challenge potential employee movement, thus the treatment effect is expected to be higher. Conversly, if the noncompete enforceability is low, then the treatment effect is expected to be lower. Based on Starr's (2019) noncompete enforceability scores, I categorize the states into high and low enforceability and analyze the treatment effect of IDD separately.

In Table 23, the same regression analysis is performed on the two subsamples representing a high or low level of noncompete enforceability. In columns 1 and 2, there is a 1 percent increase in the level of MFF patents when noncompete enforceability is high, but not a significant increase when the noncompete enforceability is low. Although the magnitude of the treatment effect is the same in high-noncompete enforceability states, the significance level is much higher. The result suggests that noncompete enforceability seems to have a strong impact on firms' technology sourcing activities through the MFF. When noncompete enforceability is low, firms expect that they can still hire away employees even when IDD is in place. Thus they have less incentive to obtain human capital through acquisition. In columns 3 and 4, there seems to be no significant treatment effect for the MFT patents, no matter the noncompete enforceability is high or low. Having IDD in place itself may not be necessary for firms to be willing to substitute with external technology sourcing. It is the fact that firms are facing difficulty in hiring new inventors that encourages them to pursue more external technology sourcing, and especially through acquisition.

**Table 23: Comparing states with different levels of enforceability**

| VARIABLES | (1)<br>MFF | (2)<br>MFF | (3)<br>MFT | (4)<br>MFT |
|---|---|---|---|---|
| Enforceability | High | Low | High | Low |
| IDD | 0.01*** | -0.00 | -0.00 | 0.01 |
| | (0.01) | (0.00) | (0.01) | (0.01) |
| Internal patent | -0.01* | -0.00 | 0.08*** | 0.10*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Sales | -0.01*** | -0.01*** | -0.00* | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Employment | 0.05*** | 0.06*** | 0.01 | -0.00 |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Non-compete index | -0.00 | -0.01* | 0.01*** | 0.00 |
| | (0.01) | (0.00) | (0.00) | (0.01) |
| Constant | -0.05 | -0.23*** | -0.07*** | -0.14*** |
| | (0.05) | (0.07) | (0.03) | (0.06) |
| | | | | |
| Observations | 94,524 | 111,876 | 94,524 | 111,876 |
| R-squared | 0.24 | 0.23 | 0.26 | 0.28 |
| Year*State FE | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| VCE cluster | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20
Note: This table looks at the treatment effect of IDD in different subsamples based on the level of enforceability from Starr (2019). The states are defined to be either high or low enforceability based on the enforceability score. Columns 1 and 3 are for high enforceability and columns 2 and 4 are for low enforceability. The result suggests that the treatment effect is stronger under high enforceability and weaker under low enforceability.

### 4.4.4 Treatment effect estimation based on the matched sample

Due to the common concern on the imbalance between the control and treatment groups in the difference-in-difference analysis, especially when considering firms located in different states, I further use the PSM approach to create matched sample. The resulting sample has better balance between the two groups, thus provides better estimation of the treatment effect.

In Table 24, the analysis is performed on the matched sample after PSM. Columns 1 to 3 look at the MFF patents, and columns 4 to 6 look at the MFT patents. In column 1, the matched sample shows an even stronger treatment effect supporting the substitution effect. There is on average 2 percent increase in the level of external technology sourcing through the MFF, which is stronger both in the magnitude and in the significance level compared to the original analysis based on the whole sample. The treatment effect is stronger in states with high noncompete enforceability (column 2), and is weaker in states with low noncompete enforceability (column 3). For the MFT, the matched sample also did not show any significant treatment effect.

**Table 24: Treatment effect estimation based on the matched sample**

| VARIABLES | (1)<br>MFF | (2)<br>MFF | (3)<br>MFF | (4)<br>MFT | (5)<br>MFT | (6)<br>MFT |
|---|---|---|---|---|---|---|
| | All | High | Low | All | High | Low |
| IDD | 0.02*** | 0.03** | 0.01* | 0.01 | 0.01+ | 0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Internal patent | -0.01** | -0.01 | -0.01+ | 0.08*** | 0.08*** | 0.08*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Sales | -0.01*** | -0.01*** | -0.01*** | 0.00+ | 0.00 | 0.00** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Employment | 0.05*** | 0.05*** | 0.06*** | -0.01* | -0.00 | -0.01+ |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) | (0.01) |
| Noncompete index | -0.00 | 0.00 | -0.01*** | 0.00 | 0.01*** | -0.00 |
| | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | -0.14*** | -0.03 | -0.16** | -0.10*** | -0.11*** | -0.13*** |
| | (0.04) | (0.06) | (0.09) | (0.03) | (0.04) | (0.06) |
| | | | | | | |
| Observations | 210,324 | 116,487 | 93,837 | 210,324 | 116,487 | 93,837 |
| R-squared | 0.23 | 0.24 | 0.27 | 0.26 | 0.28 | 0.30 |
| Year FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| State FE | YES | YES | YES | YES | YES | YES |
| VCE cluster | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

Note: This table shows the treatment effect estimation based on the matched sample using propensity score matching. After matching, the sample is more balanced between the treatment and control groups, thus provides a more accurate estimation of the treatment effect. Columns 1 and 4 look at the whole sample, columns 2 and 5 look at states with high noncompete enforceability, columns 3 and 6 look at states with low noncompete enforceability. Consistent with the main analysis, but with stronger treatment effect, there is about 2 percent increase in MFF patents with IDD treatment. The treatment effect is higher when the state noncompete enforceability is high, and is lower when the state noncompete enforceability is low.

## *4.5 Conclusion and Discussion*

Although there are different choices of modes for external technology sourcing (Arora, Cohen, et al., 2016; Grigoriou & Rothaermel, 2017; Kapoor & Klueter, 2015; Moeen, 2017), there are also different ways of conducting internal innovation (Hill & Rothaermel, 2003; Zucker & Darby, 1997). This study suggests that hiring new inventors is one way in which firms can access new technologies and technical capabilities, thus being potential substitutes for other modes of external technology sourcing. In addition, hiring complements external sourcing because it brings absorptive capacity (Cohen & Levinthal, 1990) and insider information that facilitates the evaluation of external targets and subsequent integration.

This study focuses on two different modes of external technology sourcing: the market for firms (MFF) and the market for technology (MFT). The empirical analyses show that, when the external supply of employees is constrained, the substitution effect dominates and firms are likely to obtain new technology externally through the MFF, but not through the MFT. The difference between the MFF and the MFT is likely due to the differences between the MFF and MFT in sourcing technical capabilities.

This study incorporates patent reassignment information from the USPTO and identifies three types of patents: internal patents, MFT patents, and MFF patents. It represents an advance in patent matching compared to that of prior studies (e.g., Arora, Belenzon, & Rios, 2014), and is the first large scale study to match the patent filing and reassignment information to the universe of U.S. manufacturing sectors. The large-scale matching of three different categories of patents enables me to study firms' technology-sourcing strategy in detail.

However, there are limitations to this study that provide opportunities for future research. First, this study does not examine the outcomes of these different types of technology-sourcing strategies, focusing only on firms' decisions to pursue them. Thus, we do not know whether the compensation for hiring by external technology sourcing results in better innovation outcomes. Second, I focus on U.S. patenting activities and within the same state in which the acquiring firms operate. Firms may also have considerable technology-sourcing and talent acquisition activities outside the state or even on a global level, but in the empirical analysis of this study, I only consider patents within the same state of the establishment.

This study opens avenues for future studies. While hiring an employee almost always have lower costs than acquiring a company, is hiring always the optimal choice that firms pursue? Or, when firms are facing the different choices between internal versus external, which is the optimal strategy? In this study I do not look at hiring activities specifically, but only assess the ability of hiring through the state adoption of IDD or the state noncompete enforceability. A further understanding of these problems will create a more concrete picture of firms' technology-sourcing strategies.

# 5. Conclusion

My dissertation investigates the relationship between external technology sourcing and firms' position on resources and capabilities under turbulence environment. In the first chapter, I show that in the steady state, firms that possess valuable complementary assets (trademarks) are more likely to stick to internal innovation. But they are more likely to commercialize external innovation when they are entering new markets. In the second chapter, I show that when firms commercialize external technology and entering a new market at the same time, they are actually more likely (and better off) to develop new complementary assets. This capability to develop new complementary assets for the new market and external technology may come from the fact that they already hold valuable complementary assets themselves. In the last chapter, I show that by hiring new employees, firms can obtain both new technology and capabilities. When facing an exogenous constraint in hiring, firms are likely to substitute with external technology sourcing, but more likely to use acquisition which brings the firm both new technology and new capabilities.

Overall, my dissertation suggests that when firms pursue external technology sourcing, especially in turbulence environments, capabilities to develop new technologies, as well as the complementary assets that fit best with the external technology and environment, are more important than existing resources. The requisite capabilities may raise from firms' experiences in building existing resources and assets, from hiring new employees. When internal development is not viable, they may also come from externally, which means firms obtain the external technology as well as the necessary capabilities that are associated with the technology altogether.

# Appendix I

Table A1. Trademark information by industry (new-to-the-market and standalone)

| Industry | NAICS3 | Freq | %NewTM | %OldTM | %TMasset | %Topbrand |
|---|---|---|---|---|---|---|
| Food | 311 | 31 | 0.52 | 0.65 | 0.32 | 0.03 |
| Beverage | 312 | 6 | 0.67 | 0.50 | 0.33 | 0.17 |
| Textile Mills | 313 | 9 | 0.56 | 0.67 | 0.44 | 0.00 |
| Textile Product Mills | 314 | 10 | 0.10 | 0.30 | 0.00 | 0.00 |
| Apparel | 315 | 8 | 0.63 | 0.63 | 0.38 | 0.00 |
| Leather | 316 | 1 | 0.00 | 0.00 | 0.00 | 0.00 |
| Wood Product | 321 | 5 | 0.20 | 0.60 | 0.20 | 0.00 |
| Paper | 322 | 16 | 0.31 | 0.56 | 0.19 | 0.00 |
| Printing | 323 | 8 | 0.13 | 0.25 | 0.00 | 0.00 |
| Petroleum and Coal | 324 | 6 | 0.17 | 0.33 | 0.17 | 0.17 |
| Chemical | 325 | 58 | 0.59 | 0.66 | 0.29 | 0.02 |
| Pharmaceutical and Medicine | 326 | 37 | 0.49 | 0.46 | 0.22 | 0.03 |
| Nonmetallic Mineral | 327 | 18 | 0.56 | 0.50 | 0.28 | 0.00 |
| Primary Metal | 331 | 18 | 0.28 | 0.39 | 0.28 | 0.00 |
| Fabricated Metal | 332 | 31 | 0.26 | 0.45 | 0.16 | 0.00 |
| Machinery | 333 | 49 | 0.35 | 0.45 | 0.18 | 0.00 |
| Computer and Electronics | 334 | 127 | 0.46 | 0.50 | 0.16 | 0.02 |
| Electrical Equipment | 335 | 58 | 0.45 | 0.41 | 0.21 | 0.02 |
| Transportation Equipment | 336 | 42 | 0.45 | 0.45 | 0.17 | 0.00 |
| Furniture | 337 | 26 | 0.31 | 0.42 | 0.15 | 0.00 |
| Miscellaneous | 339 | 64 | 0.52 | 0.63 | 0.27 | 0.00 |

Note: sample weights not applied

# Appendix II

## *Matching USPTO patent data to NETS companies*

The study is based on the universe of companies included in the 2013 National Establishment Time Series Data. To obtain information for the innovation activities and technology acquisitions, the companies are matched to the patent grant and assignment data from USPTO.

The patent grant data is from the 2013 version of the Harvard Patent Inventor Database (Lai et al., 2011). The patent assignment data is from the 2016 version of the USPTO Patent Assignment Dataset (Marco et al., 2015).

### Problems with traditional firm name matching

String matching is the common way to merge two datasets identified by firm names. For the patent data, string matching is challenging because firm names are often documented in a non-standardized format in the patent documents. The NBER patent data represents one of the earlier (and most used) effort to standardize assignee names in the patent data and match the USPTO patent data to the companies listed in Compustat (Hall Jaffe and Trajtenberg, 2001). More recent development of string matching methodologies involves a Bayesian supervised learning approach (Lai et al., 2011) or various methods based on the different editing distance between two strings.

While string matching is an effective way of merging different datasets, it is not efficient due to large variants of firm names within the patent data or the target data. And this differs by firm size, brand value, etc.

Name differentiator: In an early investigation in this study, it is found that small firms tend to stick to one names in different government filings, while large firms tend to have more variants, and use different names for different branches or subsidiaries. For example, "IND," "INT," "MFG," "GROUP" are considered as different firms if they are missing from one side of the matching for small firms, but for large firms, they are not an issue.

Abbreviations: Firms may use different versions of abbreviations in one sample, but the full form in another sample. For example, "AUTOMATION" is written as "ATMN," "MANUFACTURING" is written as "MFG." While this difference can be captured by tools like the editing distance, it is often omitted of not accurate.

Misspellings (especially in the patent data): In the patent data, it is possible that a word is misspelled – and there can be many different ways of misspelling by omitting a letter or replacing with another. This makes it difficult to standardize firm names by abbreviation as mentioned in (2).

Additional information: In the patent data, sometimes firm names are combined with its address as the assignee. This results in difficulty in using editing distance.

## Addressing the problem and matching procedure

To address the issues mentioned above with traditional matching, a semi-manual matching approach is adapted in this study. The matching procedure is as follows:

Standardize all firm names from the patent data and the NETS data following the NBER procedure (Hall Jaffe and Trajtenberg, 2001).

Use the first long word (number of letters >=3) in the patent data to search for all firms that contain the first word. This forms the basis for subsequent matching. Note that this also implies the matching procedure assumes no abbreviation in the first word (which is often the case) and also no misspelling in the first word (it is hard to distinguish misspelling from a different word in the first word because it often represents the brand of the company).

Using different ways of calculating the editing distance as well as checking on other words within the firm name to generate probabilities of matching. As an example if a similar approach, refer to He et al (2016).

Combining different recommendations made by different matching algorithms, facilitated with manual checking to resolve the problems as mentioned in the previous section.

Check on relatively large firms that have a common brand name, and allow variations in its firm names.

### Additional notes for matching

This matching procedure allows matching by firm name with variants that are closest to them. Because the NETS data includes all establishments (parent firms and their subsidiaries), it allows capturing patents filed or assigned under different variants of the firm name. It also allows identifying patents that are filed by parent firm itself or by an externally acquired subsidiary, which is one of the key information in this study.

## *Categorizing establishments and patents*

The matched patents from both the USPTO patent assignment data and the patent grant information from the Harvard Patent Inventor Database are further categorized into three types based on its origin: internally developed patent (*internal*), externally developed patent (*external*), and acquired patent through company acquisition (*acquired*). To distinguish between patents acquired externally from patents that acquired through company acquisition, further information of firm ownership structure if obtained through the NETS data (consider the year 2010 as the benchmark), as documented below.

### Internal establishments vs. acquired establishments

The NETS data reports the US headquarters for all its establishments. For standalone companies, the headquarters will be themselves. Throughout our analysis, a firm is defined as a unique headquarter in 2010. All establishments that have been reported to be a subsidiary of a 2010-headquarter before 2011 are included, including the ones that are no longer exist (represented as missing data in 2010).

Subsidiaries are labeled as either internal or acquired by comparing the subsidiary name to the firm name. This is defined loosely because often the same first word of the names represents establishments that come from the same corporate group. String comparisons, manual matching facilitated with website search are performed to make the comparison. If the firm names are similar, the subsidiary is considered to be an internally established branch of the firm. If the firm names are largely different, the subsidiary is considered to be acquired from externally.

Externally acquired establishments are further labeled as standalone if the establishment has been standalone before acquired by the parent firm – that means the headquarter of the establishment is itself for every year before the acquisition.

Externally acquired establishments are also labeled as startups if they are standalone that have been in practice within five years before the acquisition.

## Patent categories

Both the patent grant and the patent assignment information are matched to the name of establishments. If a patent is matched to an external establishment, it is labeled as acquired patent, no matter the establishment is an initial assignee or a reassigned assignee. If a patent is matched to an internal establishment, it is labeled as an internal patent if the establishment is the original assignee, and labeled as an external patent if the establishment is a reassigned assignee.

The patent grant information is established at the time of its initial grant, and does not change when the patent is reassigned to another party. As a result, an original assigned is defined as either the granted assignee in the Harvard Patent Inventor Database or one that is the same as the original assignee in the USPTO Patent Assignment database. The latter is accomplished by comparing assignee to the initial patent application and grant files from USPTO.

A patent may be matched to a firm in different ways – e.g. as initial applicants and assignee, or as reassigned assignee to either the same or a different establishment affiliated to the same firm. Treating each of these scenarios as an independent patent will result in double counting. For each firm (US headquarter), each patent is counted only once, and priority is given to original assignees. That means, if a patent is an internal patent to any of the subsidiary establishments of a firm, it is categorized as an internal patent, and its reassignment information is not considered. If a patent is not an internal patent to any of the subsidiary establishments of a firm, it is an external patent, and only its first reassignment to any of the subsidiary establishments is retained. If this reassignment is to both an internal and an external subsidiary at the same time, the assignment to an internal subsidiary is retained.

As a result, each firm has only one count for each patent that is associated with this firm. And each associated patent is either an internal, external or acquired patent.

### *Technology*

Patents associated with technology is identified by keyword search from the USPTO patent search site. Three different technologies are considered currently:

Nanotechnology: “NANOTECHNOLOGY” or “NANOMATERIAL”

RNA interference: “RNA INTERFERENCE” or “MICRO RNA”

All patents pulled up through the keyword search are considered technology relevant patents.

# References

Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. (2004). Knowledge Transfer Through Inheritance: Spinout Generation, Development, and Survival. *Academy of Management Journal*, *47*(4), 501–522.

Agarwal, R., & Helfat, C. E. (2009). Strategic Renewal of Organizations. *Organization Science*, *20*(2), 281–293.

Ahuja, G., & Katila, R. (2001). Technological Acquisitions and the Innovation Performance of Acquiring Firms: A Longitudinal Study. *Strategic Management Journal*, *22*(3), 197–220.

Ajay Agrawal, Joshua Gans, & Avi Goldfarb. (2018). Prediction Machines: The Simple Economics of Artificial Intelligence. In *Harvard Business Review Press*.

Akerlof, G. (1970). The Market for Lemons. *Quarterly Journal of Economics*, *84*(3), 488–500.

Allegrezza, S., & Guard Rauchs, A. (1999). The Determinants of Trademark Deposits: an Econometric Investigation (A Case Study of the Benelux). *Economie Appliquee*, *52*(2), 51–68.

Arora, A., Bei, X., & Cohen, W. M. (2016). Why Firms Trademark (or not): Evidence from the US Trademark Data. *Academy of Management Proceedings*, *2016*(1), 17249. Briarcliff Manor, NY 10510: Academy of Management.

Arora, A., Belenzon, S., & Rios, L. A. (2014). Make, Buy, Organize: The Interplay between Research, External Knowledge, and Firm Structure. *Strategic Management Journal*, *35*(3), 317–337.

Arora, A., & Ceccagnoli, M. (2006). Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing. *Management Science*, *52*(2), 293–308.

Arora, A., Cohen, W. M., & Walsh, J. P. (2016). The Acquisition and Commercialization of Invention in American Manufacturing: Incidence and Impact. *Research Policy*, *45*(6), 1113–1128.

Arora, A., Fosfuri, A., & Gambardella, A. (2001). *Markets for Technology*.

Arora, A., & Gambardella, A. (1994a). Evaluating technological information and utilizing it. *Journal of Economic Behavior & Organization*, *24*(1), 91–114.

Arora, A., & Gambardella, A. (1994b). The Changing Technology of Technological Change: General and Abstract Knowledge and the Division of Innovative Labour. *Research Policy*, *23*(5), 523–532.

Arora, A., & Merges, R. P. (2004). Specialized supply firms, property rights and firm boundaries. *Industrial and Corporate Change*, *13*(3), 451–475.

Arora, A., & Nandkumar, A. (2012). Insecure advantage? Markets for technology and the value of resources for entrepreneurial ventures. *Strategic Management Journal*, *33*(3), 231–251.

Athey, S., & Imbens, G. W. (2018). *Design-Based Analysis in Difference-in-Difference Settings with Staggered Adoption*.

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120.

Barney, J. B. (1986). Strategic Factor Markets: Expectations, Luck, and Business Strategy. *Management Science*, *32*(10), 1231–1241.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, *27*(6), 643–650.

Bayus, B. L., & Agarwal, R. (2007). The Role of Pre-Entry Experience, Entry Timing, and Product Technology Strategies in Explaining Firm Survival. *Management Science*, *53*(12), 1887–1902.

Bei, X. (2018). *Boundary Choices in Innovation: How does Availability of Hiring Affect Firms' Technology Sourcing Strategies?*

Bei, X. (2019). Trademarks, Specialized Complementary Assets, and the External Sourcing of Innovation. *Research Policy*, 1–13.

Bertrand, M., & Mullainathan, S. (2003). Enjoying the Quiet Life? Corporate Governance and Managerial Preferences. *Journal of Political Economy*, *111*(5), 1043–1075.

Bertrand, O. (2009). Effects of Foreign Acquisitions on R&D Activity: Evidence from Firm-Level Data for France. *Research Policy*, *38*(6), 1021–1031.

Block, J. H., De Vries, G., Schumann, J. H., & Sandner, P. (2014). Trademarks and Venture Capital Valuation. *Journal of Business Venturing*, *29*(4), 525–542.

Brusoni, S., Jacobides, M. G., & Prencipe, A. (2009). Strategic Dynamics in Industry Architectures and the Challenges of Knowledge Integration. *European Management Review*, *6*(4), 209–216.

Brusoni, S., Prencipe, A., & Pavitt, K. (2001). Knowledge Specialization, Organizational Coupling, and the Boundaries of the Firm: Why Do Firms Know More Than They Make? *Administrative Science Quarterly*, *46*(4), 597.

Capron, L., Dussauge, P., & Mitchell, W. (1998). Resource Redeployment Following Horizontal Mergers and Acquisitions in Europe and North America, 1988–1992. *Strategic Management Journal*, *19*(7), 631–661.

Capron, L., & Mitchell, W. (2009). Selection Capability: How Capability Gaps and Internal Social Frictions Affect Internal and External Strategic Renewal. *Organization Science*, *20*(2), 294–312.

Capron, L., & Mitchell, W. (2012). Build, Borrow, or Buy: Solving the Growth Dilemma. *Harvard Business Review*.

Cassiman, B., & Veugelers, R. (2006). In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science*, *52*(1), 68–82.

Cattani, G. (2005). Preadaptation, Firm Heterogeneity, and Technological Performance: A Study on the Evolution of Fiber Optics, 1970–1995. *Organization Science*.

Ceccagnoli, M., Graham, S. J. H. H., Higgins, M. J., Lee, J., Higginsy, M. J., & Leez, J. (2010). Productivity and the Role of Complementary Assets in Firms' Demand for

Technology Innovations. *Industrial and Corporate Change*, *19*(3), 839–869.

Ceccagnoli, M., & Jiang, L. (2013). The Cost of Integrating External Technologies: Supply and Demand Drivers of Value Creation in the Markets for Technology. *Strategic Management Journal*, *34*, 404–425.

Chatterji, A., & Patro, A. (2014). Dynamic Capabilities and Managing Human Capital. *Academy of Management Perspectives*, *28*(4), 395–408.

Christensen, C. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business Press.

Coase, R. H. (1937). The Nature of the Firm. *Economica-New Series*, *4*(16), 386–405.

Coff, R. W. (1997). Human Assets and Management Dilemmas: Coping with Hazards on the Road to Resource-Based Theory. *Academy of Management Review*, *22*(2), 374–402.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128–152.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2000). Protecting Their Intellectual Assets◎: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (Or Not). *NBER Working Paper Series*, 50.

Colombo, M. G., Grilli, L., & Piva, E. (2006). In Search of Complementary Assets: The Determinants of Alliance Formation of High-Tech Start-Ups. *Research Policy*, *35*(8 SPEC. ISS.), 1166–1199.

Coumau, J., Fabius, V., & Meyer, T. (2015). Incumbents as Attackers◎: Brand-Driven Innovation. In *McKinsey&Company*.

Coyle, J. F., & Polsky, G. D. (2013). Acqui-Hiring. *Duke Law Journal*, *63*(2), 281–346.

Cozzolino, A., & Rothaermel, F. T. (2018). Discontinuities, Competition, and Cooperation: Coopetitive Dynamics between Incumbents and Entrants. *Strategic Management Journal*, (September 2017), 1–33.

Crass, D. (2014). Which Firms Use Trademarks -- and Why? Representative Firm-Level Evidence from Germany. *ZEW Discussion Papers*.

Criscuolo, P., Laursen, K., Reichstein, T., & Salter, A. (2018). Winning Combinations: Search Strategies and Innovativeness in the UK. *Industry and Innovation*, *25*(2), 115–143.

Decker, C., & Baade, A. (2016). Consumer Perceptions of Co-Branding Alliances: Organizational Dissimilarity Signals and Brand Fit. *Journal of Brand Management*, *23*(6), 648–665.

Dencker, J. C., Gruber, M., & Shah, S. K. (2009). Pre-Entry Knowledge, Learning, and the Survival of New Firms. *Organization Science*, *20*(3), 516–537.

Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. (2012). Microfoundations of Routines and Capabilities: Individuals, Processes, and Structure. *Journal of Management Studies*, *49*(8), 1351–1374.

Fosfuri, A., & Giarratana, M. S. (2009). Masters of War: Rivals' Product Innovation and New Advertising in Mature Product Markets. *Management Science*, *55*(2), 181–191.

Fosfuri, A., Giarratana, M. S., & Luzzi, A. (2008). The Penguin Has Entered the Building: The Commercialization of Open Source Software Products. *Organization Science*, *19*(2), 292–305.

Foss, N. J. (1996). Knowledge-Based Approaches to the Theory of the Firm: Some Critical Comments. *Organization Science*, *7*(5), 470–476.

Fuller, A. W., & Thursby, M. C. (2008). Technology commercialization: Cooperative versus competitive strategies. In *Technological Innovation: Generating Economic Results* (Vol. 18, pp. 227–250).

Gambardella, A., Giuri, P., & Luzzi, A. (2007). The Market for Patents in Europe. *Research Policy*, *36*(8), 1163–1183.

Gans, J. S., & Stern, S. (2003). The Product Market and the Market for "Ideas": Commercialization Strategies for Technology Entrepreneurs. *Research Policy*, *32*(2), 333–350.

Gao, G. (Gordon) G. (Gordon), & Hitt, L. M. (2012). Information Technology and Trademarks: Implications for Product Variety. *Management Science*, *58*(6), 1211–1226.

Garmaise, M. J. (2011). Ties That Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment. *Journal of Law, Economics, and Organization*, *27*(2), 376–425.

Godfrey, E. R. (2004). Inevitable Disclosure of Trade Secrets: Employee Mobility v. Employer's Rights. *Journal of High Technology Law*, *3*.

Gotsch, M., & Hipp, C. (2012). Measurement of Innovation Activities in the Knowledge-Intensive Services Industry: A Trademark Approach. *The Service Industries Journal*, *32*(13), 2167–2184.

Graham, S. J. H., Hancock, G., Marco, A. C., & Myers, A. F. (2013). The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights. *Journal of Economic & Management Strategy*, *22*(4), 669–705.

Grigoriou, K., & Rothaermel, F. T. (2017). Organizing for Knowledge Generation: Internal Knowledge Networks and the Contingent Effect of External Knowledge Sourcing. *Strategic Management Journal*, *38*(2), 395–414.

Hamel, G. (1991). Competition for Competence and Interpartner Learning within International Strategic Alliances. *Strategic Management Journal*, *12*(1 S), 83–103.

Harris, J. O. (2000). The Doctrine of Inevitable Disclosure◎: A Proposal to Balance Employer and Employee Interests. *Washington University Law Review*, *78*(1), 325–345.

Helfat, C. E. (1994). Evolutionary Trajectories in Petroleum Firm R&D. *Management Science*, *40*(12), 1720–1747.

Helfat, C. E. (1997). Know-how and Asset Complementarity and Dynamic Capability Accumulation: The Case of R&D. *Strategic Management Journal*, *18*(5), 339–360.

Helfat, C. E., & Eisenhardt, K. M. (2004). Inter-Temporal Economies of Scope, Organizational Modularity, and the Dynamics of Diversification. *Strategic Management Journal*, *25*(1), 1217–1232.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M. a, Singh, H., Teece, D. J., & Winter, S. G. (2007). *Dynamic Capabilities: Understanding Strategic Change in Organizations* (Vol. 18). Malden, MA: Blackwell.

Helfat, C. E., & Lieberman, M. B. (2002). The Birth of Capabilities: Market Entry and the Importance of Pre-history. *Industrial and Corporate Change*, *11*(4), 725–760.

Helfat, C. E., & Raubitschek, R. S. (2000). Product Sequencing: Co-Evolution of Knowledge , Capabilities and Products. *Strategic Management Journal*, *21*(10/11), 961–979.

Henderson, R. M., & Clark, K. B. (1990). Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly*, *35*(1), 9–30.

Higgins, M. J., & Rodriguez, D. (2006). The Outsourcing of R&D through Acquisitions in the Pharmaceutical Industry. *Journal of Financial Economics*, *80*(2), 351–383.

Hill, C. W. L., & Rothaermel, F. T. (2003). The Performance of Incumbent Firms in the Face of Radical Technological Innovation. *Academy of Management Review Tripsas & Gavetti*, *28*(2), 257–274.

Hoang, H., & Rothaermel, F. T. (2010). Leveraging Internal and External Experience: Exploration, Exploitation, and R&D Project Performance. *Strategic Management Journal*, *31*(7), 734–758.

Hugo, V., Ferreira, S., & Godinho, M. (2011). Building an Innovation Function with Patents and Trademarks: Evidence from Portuguese Regional Innovation Systems. *DRUID*.

Inkpen, A. C. (1998). Learning and Knowledge Acquisition through International Strategic Alliances. *The Academy of Management Executive*, *12*(4), 70–80.

Jacobides, M. G., Knudsen, T., & Augier, M. (2006). Benefiting from Innovation: Value Creation, Value Appropriation and the Role of Industry Architectures. *Research Policy*, *35*(8 SPEC. ISS.), 1200–1221.

Judkins, D. (1990). Fay's Method for Variance Estimation. *Journal of Official Statistics*, Vol. 6, pp. 223–239.

Kale, P., & Singh, H. (2007). Building Firm Capabilities through Learning: The Role of the Alliance Learning Process in Alliance Capability and Firm-Level Alliance Success. *Strategic Management Journal*, *28*(10), 981–1000.

Kapoor, R. (2013). Persistence of Integration in the Face of Specialization: How Firms Navigated the Winds of Disintegration and Shaped the Architecture of the Semiconductor Industry. *Organization Science*, *24*(4), 1195–1213.

Kapoor, R., & Furr, N. R. (2015). Complementarities and Competition: Unpacking the Drivers of Entrants' Technology Choices in the Solar Photovoltaic Industry. *Strategic Management Journal*, *36*, 416–436.

Kapoor, R., & Klueter, T. (2015). Decoding the Adaptability--Rigidity Puzzle: Evidence From Pharmaceutical Incumbents' Pursuit of Gene Therapy and Monoclonal Antibodies. *Academy of Management Journal*, *58*(4), 1180–1207.

Karim, S., & Mitchell, W. (2000). Path-Dependent and Path-Breaking Change: Reconfiguring Business Resources Following Acquisitions in the U.S. Medical Sector, 1978–1995. *Strategic Management Journal*, *21*(1011), 1061–1081.

Kim, D.-J., & Kogut, B. (1996). Technological Platforms and Diversification. *Organization Science*, *7*(3), 283–301.

Klasa, S., Ortiz-Molina, H., Serfling, M. A., & Srinivasan, S. (2017). Protection of Trade Secrets and Capital Structure Decisions. In *SSRN Electronic Journal*.

Klepper, S., & Simons, K. L. (2000). Dominance by Birthright: Entry of Prior Radio Producers and Competitive Ramifications in the US Television Receiver Industry. *Strategic Management Journal*, *21*(10), 997–1016.

Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, *3*(3), 383–397.

Kraatz, M. S., & Zajac, E. J. (2001). How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence. *Organization Science*, *12*(5), 632–657.

Laursen, K., & Salter, A. (2004). Searching High and Low: What Yypes of Firms Use Universities as a Source of Innovation? *Research Policy*, *33*(8), 1201–1215.

Laursen, K., & Salter, A. (2006). Open for Innovation: The Role of Openness in Explaining Innovation Performance among U.K. Manufacturing Firms. *Strategic Management Journal*, *27*(2), 131–150.

Laursen, K., & Salter, A. J. (2014). The Paradox of Openness: Appropriability, External Search and Collaboration. *Research Policy*, *43*(5), 867–878.

Lee, G. K., & Lieberman, M. B. (2010). Acquisition vs. Internal Development as Modes of Market Entry. *Strategic Management Journal*, *31*(2), 140–158.

Lee, H., & Shin, H. D. (2010). Which Subfield to Enter First? The Role of a Firm's Pre-Entry Experiences. *Journal of Business Research*.

Levin, R. C., Klevorick, A. K., Nelson, R. R., & Winter, S. G. (1987a). Appropriating the Returns from Industrial Research and Development; Comments and Discussion. *Brookings Papers on Economic Activity*, 783.

Levin, R. C., Klevorick, A. K., Nelson, R. R., & Winter, S. G. (1987b). Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity*, *3*, 784–831.

Li, G. C., Lai, R., D'Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., … Lee, F. (2014). Disambiguation and co-authorship networks of the U.S. patent inventor database (1975-2010). *Research Policy*, *43*(6), 941–955.

Love, J. H., Roper, S., & Vahter, P. (2014). Dynamic Complementarities in Innovation Strategies. *Research Policy*, *43*(10), 1774–1784.

Luo, J., Baldwin, C. Y., Whitney, D. E., & Magee, C. L. (2012). The Architecture of Transaction Networks: A Comparative Analysis of Hierarchy in Two Sectors. *Industrial and Corporate Change*, *21*(6), 1307–1335.

Mahoney, J. T. (1992). The Choice of Organizational Form: Vertical Financial Ownership Versus Other Methods of Vertical Integration. *Strategic Management Journal*, *13*(8), 559–584.

Marco, A. C., Myers, A. F., Graham, S., Agostino, P. D., & Apple, K. (2015). The USPTO Patent Assignment Dataset: Descriptions and Analysis. In *USPTO Economic Working Paper* (Vol. 2015).

Mawdsley, J. K., & Somaya, D. (2016). Employee Mobility and Organizational Outcomes. *Journal of Management*, *42*(1), 85–113.

Melnyk, V., Giarratana, M., & Torres, A. (2014). Marking Rour Trade: Cultural Factors in the Prolongation of Trademarks. *Journal of Business Research*, *67*(4), 478–485.

Mendonça, S., Pereira, T. S., & Godinho, M. M. (2004). Trademarks as an Indicator of Innovation and Industrial Change. *Research Policy*, *33*(9), 1385–1404.

Mitchell, W. (1989). Whether and When◎? Probability and Timing of Incumbents' Entry into Emerging Industrial Subfields. *Administrative Science Quarterly*, *34*(2), 208–230.

Mitchell, W., & Shaver, J. M. (2003). Who Buys What? How Integration Capability Affects Acquisition Incidence and Target Choice. *Strategic Organization*, *1*(2), 171–201.

Mitchell, W., & Singh, K. (1992). Incumbents' Use of Pre-Entry Alliances Before Expansion into New Technical Subfields of an Industry. *Journal of Economic Behavior and Organization*, *18*(3), 347–372.

Moeen, M. (2017). Entry into Nascent Industries: Disentaling a Firm's Capability Portfolio at the Time of Investment Versus Market Entry. *Strategic Management Journal*, *38*, 1986–2004.

Moeen, M., & Agarwal, R. (2017). Incubation of an Industry: Heterogeneous Knowledge

Bases and Modes of Value Capture. *Strategic Management Journal*, *38*, 566–587.

Montgomery, C. A., & Wernerfelt, B. (1988). Diversification, Ricardian Rents, and Tobin's q. *The RAND Journal of Economics*, *19*(4), 623–632.

Motohashi, K. (2008). Licensing or Not Licensing? An Empirical Analysis of the Strategic Use of Patents by Japanese Firms. *Research Policy*, *37*(9), 1548–1555.

Nelson, R. R., & Winter, S. G. (1982). An Evolutionary Theory of Economic Change. In *Cambridge MA Belknap*. Cambridge, MA: Belknap Press.

Novak, S., & Stern, S. (2008). How Does Outsourcing Affect Performance Dynamics? Evidence from the Automobile Industry. *Management Science*, *54*(12), 1963–1979.

Parmigiani, A. (2007). Why Do Firms both Make and Buy? An Investigation of Concurrent Sourcing. *Strategic Management Journal*, *28*(3), 285–311.

Parmigiani, A., & Mitchell, W. (2009). Complementarity, Capabilities, and the Boundaries of the Firm: The Impact of Within-Firm and Interfirm Expertise on Concurrent Sourcing of Complementary Components. *Strategic Management Journal*, *30*(10), 1065–1091.

Patel, P., & Pavitt, K. (1997). The Technological Competencies of the World's Largest Firms: Complex and Path-Dependent, But Not Much Variety. *Research Policy*, *26*(2), 141–156.

Penrose, E. (1959). *Theory of the Growth of the Firm*. Oxford University Press.

Pisano, G. (2006). Profiting from innovation and the intellectual property revolution. *Research Policy*, *35*, 1122–1130.

Pisano, G. P. (2017). Toward a Prescriptive Theory of Dynamic Capabilities: Connecting Strategic Choice, Learning, and Competition. *Industrial and Corporate Change*, *26*(5), 747–762.

Png, I. P. L., & Samila, S. (2015). Trade Secrets Law and Mobility: Evidence from "Inevitable Disclosure." In *Working Paper*.

Prencipe, A. (2000). Breadth and Depth of Technological Capabilities in CoPS: The Case of the Aircraft Engine Control System. *Research Policy*, *29*(7–8), 895–911.

Ragozzino, R., & Reuer, J. J. (2011). Geographic Distance and Corporate Acquisitions: Signals from IPO Firms. *Strategic Management Journal*, *32*, 876–894.

Ranft, A. L., & Lord, M. D. (2002). Acquiring New Technologies and Capabilities: A Grounded Model of Acquisition Implementation. *Organization Science*, *13*(4), 420–441.

Rao, H., & Drazin, R. (2002). Overcoming Resource Constraints on Product Innovation by Recruiting Talent from Rivals◎: A Study of the Mutual Fund Industry , 1986-94. *Academy of Management Journal*, *45*(3), 491–507.

Rosenberg, N. (1982). *Inside the Black Box: Technology and Economics* (Vol. 1). Cambridge, United Kindom: Cambridge University Press.

Rosenberg, N. (1996). Uncertainty and Technological Change. In R. Landau, R. Taylor, & G. Wright (Eds.), *The Mosaic of Economic Growth* (pp. 334–353). Stanford CA: Stanford University Press.

Rosenkopf, L., & Almeida, P. (2003). Overcoming Local Search Through Alliances and Mobility. *Management Science*, *49*(6), 751–766.

Rosenkopf, L., & Nerkar, A. (2001). Beyond Local Search: Boundary-spanning, Exploration, and Impact in the Optical Disk Industry. *Strategic Management Journal*, *22*(4), 287–306.

Rothaermel, F. T. (2001). Incumbent's Advantage through Exploiting Complementary Assets via Interfirm Cooperation. *Strategic Management Journal*, *22*(6–7), 687–699.

Rothaermel, F. T. (2018). *Strategic Management: Concepts* (4th ed.). McGraw-Hill Education.

Rothaermel, F. T., & Alexandre, M. T. (2009). Ambidexterity in Technology Sourcing: The Moderating Role of Absorptive Capacity. *Organization Science*, *20*(4), 759–780.

Rothaermel, F. T., & Hill, C. W. L. (2005). Technological Discontinuities and Complementary Assets: A Longitudinal Study of Industry and Firm Performance. *Organization Science*, *16*(1), 52–70.

Rothaermel, F. T., & Thursby, M. (2007). The Nanotech versus the Biotech Revolution: Sources of Productivity in Incumbent Firm Research. *Research Policy*, *36*(6), 832–849.

Sandner, P. G., & Block, J. (2011). The Market Value of R&D, Patents, and Trademarks. *Research Policy*, *40*(7), 969–985.

Schmoch, U. (2003). Service Marks as Novel Innovation Indicator. *Research Evaluation*, *12*(2), 149–156.

Schmoch, U., & Gauch, S. (2009). Service Marks as Indicators for Innovation in Knowledge-Based Services. *Research Evaluation*, *18*(4), 323–335.

Schumpeter, J. A. (1942). The Process of Creative Destruction. *Capitalism Socialism and Democracy*, *1*(3–4), 82–85.

Semadeni, M. (2006). Minding Your Distance: How Management Consulting Firms Use Service Marks to Position Competitively. *Strategic Management Journal*, *27*(2), 169–187.

Semadeni, M., & Anderson, B. (2010). The Follower's Dilemma: Innovation and Imitation in the Professional Services Industry. *Academy of Management Journal*, *53*(5), 1175–1193.

Singh, J., & Agrawal, A. (2011). Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. *Management Science*, *57*(1), 129–150.

Song, J., Almeida, P., & Wu, G. (2003). Learning–by–Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? *Management Science*, *49*(4), 351–365.

Starr, E. (2019). Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete. *Industrial and Labor Relations Review*.

Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal*, *17*, 21–38.

Sutherland, E. (2009). Apple's iPhone "Halo Effect" Boosts Mac Sales 16.4 Percent. *Cult of Mac*.

Teece, D. J. (1986). Profiting from Technological Innovation- Implications for Integration, Collaboration, Licensing and Public-Policy. *Research Policy*, *15*(6), 285–305.

Teece, D. J. (1988). Technological Change and the Nature of the Firm. In *Technical Change and Economic Theory*: *Vol. Chapter 12* (pp. 256–281).

Teece, D. J. (1996). Firm Organization, Industrial Structure, and Technological Innovation. *Journal of Economic Behavior and Organization*, *31*(2), 193–224.

Teece, D. J. (2006). Reflections on "Profiting from Innovation." *Research Policy*, *35*(8 SPEC. ISS.), 1131–1146.

Teece, D. J. (2010). Technological Innovation and the Theory of the Firm: The Role of Enterprise-Level Knowledge, Complementarities, and (Dynamic) Capabilities. In *Handbook of the Economics of Innovation* (1st ed., Vol. 1). Elsevier B.V.

Teece, D. J., & Pisano, G. (1994). The Dynamic Capabilities of Firms: An Introduction. *Industrial and Corporate Change*, *3*, 537–557.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509–533.

Trajtenberg, M., Henderson, R., & Jaffe, A. (1997). University Versus Corporate Patents: A Window On The Basicness Of Invention. *Economics of Innovation and New Technology*, *5*(1), 19–50.

Tripsas, M. (1997). Unraveling the Process of Creative Destruction: Complementary Assets and Incumbent Survival in the Typesetter Industry. *Strategic Management Journal*, *18*(6), 119–142.

Tripsas, M., & Gavetti, G. (2000). Capabilities, cognition, and inertia: Evidence from digital imaging. *Strategic Management Journal*, *21*(10–11), 1147–1161.

Tushman, M. L., & Anderson, P. (1986). Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly*, *31*(3), 439–465.

Tzabbar, D. (2009). When Does Scientist Recruitment Affect Technological Repositioning? *Academy of Management Journal*, *52*(5), 873–896.

Tzabbar, D., Aharonson, B. S., & Amburgey, T. L. (2013). When Does Tapping External Sources of Knowledge Result in Knowledge Integration? *Research Policy*, *42*(2), 481–494.

Vermeulen, F., & Barkema, H. (2001). Learning through Acquisitions. *Academy of Management Journal*, *44*(3), 457–476.

von Hippel, E. (1990). Task Partitioning:An Innovation Process Variable. *Research Policy*, *19*(5), 407–418.

Wernerfelt, B. (1984). A Resource-based View of the Firm. *Journal of Strategic Management*, *5*(June 1982), 171–180.

West, J., & Bogers, M. (2014). Leveraging External Sources of Innovation: A Review of Research on Open Innovation. *Journal of Product Innovation Management*, *31*(4), 814–831.

Williamson, O. E. (1975). The Organizational Failures Framework. In *Markets and Hierarchies: Analysis and Antitrust Implications* (pp. 20–40). New York: The Free Press.

Williamson, O. E. (1985). *The Economics Instiutions of Capitalism*. New York: Free Press.

Williamson, O. E. (1991). Comparative Economic Organization: The Analysis of Discrete Structural Alternatives. *Administrative Science Quarterly*, *36*(2), 269–296.

Winter, S. G. (1987). Knowledge and Competence as Strategic Assets. In *The Competitive Advantage*.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*, 991–995.

Wu, B., Wan, Z., & Levinthal, D. A. (2014). Complementary Assets as Pipes and Prisms: Innovation Incentives and Trajectory Choices. *Strategic Management Journal*, *35*(9), 1257–1278.

Younge, K. A., Tong, T. W., & Fleming, L. (2015). How Anticipated Employee Mobility Affects Acquisition Likelihood: Evidence from a Natural Experiment. *Strategic Management Journal*, *36*, 686–708.

Zucker, L. G., & Darby, M. R. (1997). Present at the Biotechnological Revolution: Transformation of Technological Identity for a Large Incumbent Pharmaceutical Firm. *Research Policy*, *26*(4–5), 429–446.

## Biography

Xiaoshu Bei received her bachelor's degree in Biomedical Engineering (2008) from Zhejiang University, China. She also received her master's degree in Genetics (2011) and Economics (2013) from Duke University. To date, she has published interdisciplinary work in journals including Nature Genetics (Otto et al., 2010), PLoS One (Zheng et al., 2010), Health Affairs (Ridley, Bei, and Liebman, 2016), and Research Policy (Bei, 2019), etc.