AN ABSTRACT OF THE DISSERTATION OF

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Innovation is critical for firm growth and survival. Thus, how much value firms create and capture from their innovative activities has been interest of scholars. This dissertation explores three important questions on this topic to which extant literature has paid little attention. First, I examine how the external threat caused by a bankruptcy event in an industry affect industry firms' innovative activities. Although extant research has examined how firm specific threats (e.g., firm's own bankruptcy risk and operating performance) affect firm innovative activities, little is known about how the common threat in an industry affects firm innovative activities. Drawing on threat-rigidity theory, I propose that the threat caused by bankruptcy leads firms to reduce innovative activities and that this effect may depend on firm's own situation – firm's own bankruptcy risk. Second, I examine how trade secrecy helps firms capture value from innovative activities. Despite trade secrecy's importance and calls to examine factors that moderate the effectiveness of trade secrecy, there have been few empirical studies of when trade secrecy is most effective. I propose that trade secrecy may have a positive effect on firm financial returns to R&D activities and that this effect is contingent upon concurrent use of other appropriation mechanisms and industrial conditions. Third, I examine how firms can capture more value from innovative activities by building on its own inventions – generative appropriation. I propose that technological knowledge dispersion has a negative effect on generative appropriation while geographic knowledge dispersion has a curvilinear effect; I also propose that these effects are stronger when environmental technology opportunities are smaller. Overall, the findings of this study supported my hypotheses.

Knowledge Appropriation and Inventive Productivity

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Major Professor, representing Business Administration

Dean of the College of Business

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Yohan Choi, Author

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CONTRIBUTION OF AUTHORS

Dr. Jeffrey Barden gave advice on theory development of Chapter 3 and 4. Dr. Sam Yul Cho and Dr. Jonathan Arthurs gave advice on theory development of Chapter 2 and 3. With their advice, I was able to refine my theory.

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DEDICATION

I would like to dedicate my dissertation to my family – Taekwang Choi, Soonboon Kim, and Sunyoung Choi – who have been supporting me during this journey.

1. GENERAL INTRODUCTION

Innovation is critical for firm growth and survival (Baumol 2002; Schumpeter 1942) because innovation, which is often valuable and rare (Barney 1991), becomes the source of competitive advantage (Porter 1992). Thus, how much value firms create and capture from their innovative activities has been interest of scholars and practitioners. In this dissertation, I explore three important questions about firm's value creation and value capture from innovative activities to which extant literature has paid little attention. First, I examine how external environmental threat affects how firms create value from their innovative activities. Specifically, in the second chapter, by building on extant literature suggesting that firm innovative activities are dependent on external changes (e.g., Cohen and Levinthal 1989; Staw, Sandelands and Dutton 1981), I examine how the external threat caused by competitor's bankruptcy affect how firms create value from their innovative activities. Although existing literature has examined how firm specific threats such as firm's own bankruptcy risks and own operating performance affect firm's innovative activities (D'Aveni 1989; Chen and Miller 2007; Hayward and Shimizu 2006; Iyer and Miller 2008; McDonald and Westphal 2003), little is known about how the common external threat in an industry affects firm innovative activities. Thus, by drawing on threat rigidity theory (Chattopadhyay *et al.*, 2001; Ocasio, 1995; Staw *et al.*, 1981), I propose that the external threat caused by competitor's bankruptcy may threaten firms in the industry. Consequently, firms in the industry may become "rigid" and they reduce innovative activities in the post-bankruptcy period. I further propose that the effect of the external threat on firm innovative activities may depend on firm's own situation. Second, I examine how trade secrecy as an appropriation mechanism helps firms capture more value from innovative activities. Despite trade secrecy's importance and calls to examine factors that moderate the effectiveness of trade secrecy (James, Leiblein and Lu 2013), there have been surprisingly few empirical studies of when trade secrecy is most effective presumably due to its unobservability. Thus, by using the staggered implementation of a trade secret protection law, I examine the effect of trade secrecy on firm financial returns to R&D activities (hereafter firm R&D productivity). I propose that trade secrecy may have a positive effect on firm R&D productivity and that the effect of trade secrecy on firm R&D productivity may depend on concurrent use of other appropriation mechanisms and industrial conditions. Third, in the fourth chapter, I examine how firms can capture more value from innovative activities by building on its own inventions – generative appropriation. In particular, I examine how knowledge dispersion of a firm affects generative appropriation and how the effect of knowledge dispersion on generative appropriation is contingent upon environmental technology opportunities. I propose that technological knowledge dispersion may have a negative effect on generative appropriation while geographic knowledge dispersion may have a curvilinear relationship with generative appropriation; I also propose that external technology opportunities may weaken both relationships.

The findings of my studies, overall, support my hypotheses. Specifically, the findings of the second chapter show that external threat caused by a bankruptcy event reduces the firm's inventive productivity due to negative externalities of the bankruptcy and this negative effect depends on firm's own situation – the firm's own bankruptcy risk. The findings of the third chapter show that the increase in trade secret legal protection has a positive effect on firm R&D productivity but this effect is contingent upon other appropriation mechanisms and industrial conditions. The findings of the fourth chapter show that technological knowledge dispersion has a negative effect on generative appropriation while geographic knowledge dispersion has a curvilinear effect on generative appropriation; these effects are, however, stronger when external technology opportunities are smaller.

My dissertation makes contributions to innovation literature. First, I show that a common threat in an industry affects firms' behavioral changes in innovative activities. The findings extend existing literature suggesting that firm-specific threats such as firm's own bankruptcy risks and poor operating performance affect firm innovative activities. Second, I show that trade secrecy and knowledge dispersion may affect how much value firms capture from innovative activities in terms of the financial returns and the generation of derivative inventions spawned by their own inventions. Overall, my dissertation suggests that how much value firms create and capture from innovative activities not only depends on firm innovative and commercialization capabilities but also external environment and appropriation strategies.

2. THE IMPACT OF BANKRUPTCY ON COMPETITORS' INNOVATION

2.1. INTRODUCTION

Scholars have paid considerable attention to how bankruptcy events affect competitors of the bankrupt firm (Benmelech and Bergman, 2011; Ferris, Jayaraman, and Makhija, 1997; Hertzel, Li, Officer, and Rodgers, 2008; Jorion and Zhang, 2007; Lang and Stulz, 1992). This body of research has proposed a potential negative effect on competitors termed the "contagion" effect, and a potential positive effect on competitors termed the "competitive" effect. However, empirical studies suggest that there is a dominant contagion effect on competitors. Such deleterious contagion effect of bankruptcy often spreads to other firms in the same industry, leading to an immediate stock price decline (Akhigbe, Martin, and Whyte, 2005; Ferris *et al.*, 1997; Hertzel *et al.*, 2008; Lang and Stulz, 1992), poor market demand and future prospects (Akhigbe *et al.*, 2005; Lang and Stulz, 1992; Ozturk, Chintagunta, and Venkataraman, 2018), higher credit default swap spreads (Jorion and Zhang, 2007) and higher costs of debt financing (Benmelech and Bergman, 2011).

While the existing bankruptcy literature has examined how external stakeholders (i.e., equity and debt markets) respond to bankruptcy events, little is known about how *competitors* respond to an industry bankruptcy. In particular, the way competitors of the bankrupt firm (hereafter, competitors) respond to a bankruptcy event in the context of innovation may be interest of scholars, given the importance of innovation on firm survival and growth (Baumol, 2002; Schumpeter, 1942). Because firms in an industry may perceive a common threat or opportunity, they may show similar innovation activities and search behaviors in the face of an external threat (Chen and Miller, 2007; Gort and Wall, 1986; Patel and Pavitt, 1997). However, it is not clear how a bankruptcy event might affect competitors' innovation activities. On the one hand, competitors may take more risks and increase innovation activities upon bankruptcy if they perceive the dominant contagion effect of bankruptcy as potential losses (Kahneman and Tversky, 1979). On the other hand, competitors may take a conservative stance and decrease innovation activities upon bankruptcy if competitors perceive the contagion effect of bankruptcy as an uncontrollable threat (Chattopadhyay, Glick, and Huber, 2001; Ocasio, 1995; Staw, Sandelands, and Dutton, 1981). Drawing on threat-rigidity theory (Ocasio, 1995; Staw *et al.*, 1981), I propose that an external threat caused by a bankruptcy may make competitors "rigid" and conservative upon bankruptcy and that competitors may decrease innovative activities that require a commitment of considerable resources and entail non-routine procedures. Moreover, because the degree to which organizations perceive the external threat may also depend on their own situations (Ocasio, 1997), I propose that firms with higher *own* bankruptcy risks may perceive stronger threat caused by a third party's bankruptcy and they may show stronger rigid responses and reduce innovative activities.

An empirical challenge to measure the impact of bankruptcy event is the coincident industrial downturn. Thus, I employ a difference-in-differences approach; specifically, I first match competitor firms with control firms that have the most similar industry and firm level characters. Then, I examine competitors' change in innovation activities over time from three years before the bankruptcy event to three years after the bankruptcy event. My findings show that competitors' innovation and technology breadth decrease in the post-bankruptcy period, while R&D investment and technology generality remain similar. However, for competitors with higher own bankruptcy risks, R&D investment, innovation, technology breadth and technology generality all substantially decrease in the post-bankruptcy period relative to control firms. Robustness analyses show that competitors suffer from lower announcement returns upon bankruptcy and from deteriorating operating performance in the post-bankruptcy period and these findings confirm the contagion effect of a bankruptcy event. In sum, my study suggests that competitors become defensive and take conservative actions in the post-bankruptcy period. Further, competitors' conservative responses in the post-bankruptcy period are contingent upon each competitor's own bankruptcy risk.

Our study contributes to the literature in three important ways. First, in contrast with finance-based literature that has focused on external stakeholders (Akhigbe *et al.*, 2005; Benmelech and Bergman, 2011; Ferris *et al.*, 1997; Hertzel *et al.*, 2008; Jorion and Zhang, 2007; Lang and Stulz, 1992), I make a unique contribution to the bankruptcy literature by explaining competitors' response to a focal firm's bankruptcy in the context of innovation. Second, I investigate a new external threat - a bankruptcy of third parties - and extend prior studies on threat-rigidity theory, most of which use a focal firm's own performance or bankruptcy risk as a proxy for external threats (D'Aveni, 1989; Chen and Miller, 2007; Hayward and Shimizu, 2006; Iyer and Miller, 2008; McDonald and Westphal, 2003). Further, my study shows that the combined effects of internal and external threats (i.e., competitors' own bankruptcy risks and a third party's bankruptcy) lead to stronger threat-rigid responses. Third, my study extends recent studies supporting the procyclical view of firm innovation activities (Fabrizio and Tsolmon, 2014; Ouyang, 2011) by showing a negative effect of bankruptcy on industry competitors' innovation activities.

2.2. THEORY AND HYPOTHESIS

2.2.1. Organizational response to threats

Organizations adopt themselves to environmental changes because the fit between the organization and its environment may determine whether they will be able to survive in the short-term as well as in the long-term (Chandler Jr, 1962; Doty, Glick, and Huber, 1993; Miles, Snow, Meyer, and Coleman Jr, 1978). Therefore, how organizations respond to external threat has received considerable attention from management scholars (Chattopadhyay *et al.*, 2001; Dutton and Jackson, 1987; Staw *et al.*, 1981). Although organizations' response to external threats may vary depending on the decision makers' interpretation about the threats (Child, 1972; Thompson, 1967), characteristics of external threats often lead to similar patterns of organizations' responses. Specifically, organizations respond to external threats in two different ways depending on the uncertainty and uncontrollability of the threat (Chattopadhyay *et al.*, 2001). When the way that organizations can deal with an external threat is well understood – that is, the probability distribution for the success of organization's responses is well-defined – firms that perceive potential losses often initiate highly risky actions to deal with an external threat (Kahneman and Tversky, 1979). However, when outcomes of dealing with an external threat are not well understood – that is, when the external threat is perceived as uncontrollable – firms may take conservative actions to improve internal processes of the organization over which they have greater control (Ocasio, 1995; Staw *et al.*, 1981). By doing so, firms may improve its efficiency in business operations to deal with the uncertainties of external threat.

I theorize bankruptcy event as an "uncontrollable" external threat for which outcomes of responses to the threat are not well specified. The bankruptcy announcement of a focal firm in most cases has a negative influence on its competitors' business environment. Examples of such negative externalities include financial markets' downward stock price adjustment of competitors (Ferris *et al.*, 1997; Hertzel *et al.*, 2008; Lang and Stulz, 1992), a reduction in market demand (Ozturk *et al.*, 2018), adverse earnings forecasts (Akhigbe *et al.*, 2005; Lang and Stulz, 1992), an increase in credit default swap spreads of competitors (Jorion and Zhang, 2007) and greater costs of debt financing (Benmelech and Bergman, 2011). Thus, a third party's bankruptcy leads to industry-wide contagion effects; specifically, upon a bankruptcy event in an industry the stakeholders of competitors may develop a negative perception about the industry competitors irrespective of each competitor's financial health (Lang and Stulz, 1992) and the negative externalities will be imposed on all industry competitors. Because competitors have little control over a third party's bankruptcy as well as the development of negative perceptions by stakeholders, a bankruptcy event is likely to be considered an uncontrollable external threat by competitors. Further, the outcomes of competitor's externally directed responses that aim to address such negative externalities might be uncertain because stakeholders may develop a negative perception about the market in general (Shiu, Walsh, Hassan, and Shaw, 2011). Thus, when the contagion effect of a focal bankruptcy may evince a threat to competitors, competitors may respond in a threatened and rigid way by taking actions to improve its internal business processes over which they have more controls.

In the following sections, by drawing on threat-rigidity theory I explain how such uncontrollable external threats caused by bankruptcy affect competitors' innovation activities and the way they conduct innovation activities. I also discuss under what conditions competitors perceive greater threat posed by a bankruptcy event and, as a result, they show stronger threat rigid responses in terms of innovation activities.

2.2.2. Threat-rigidity theory and competitors' innovation activities

I draw on threat-rigidity theory to explain how the external threat caused by bankruptcy affect competitors' innovation activities. Consistent with prior literature, I define "threat" as a "negative situation over which one has relatively little control" (Dutton and Jackson, 1987, p. 80). Threat-rigidity theory (Chattopadhyay *et al.*, 2001; Ocasio, 1995; Staw *et al.*, 1981) suggests that organizations in the face of a threat may exhibit responses, which are rigid and inflexible in nature. A threat creates a damage-control mindset and psychological stress and anxiety for organization members (Audia and Greve, 2006) so that responses to a threat tend to exhibit risk aversion (Wiseman and Bromiley, 1996), an inward focus (Shimizu, 2007) and a pursuit of improvements in the status quo rather than a search for new opportunities. These responses lead firms to pursue efficiency while minimizing costs, restrict information processing, and emphasize the stronger control over organizational activities. These activities are meant to avoid organizational disruption and change which may exacerbate problems arising from the threat.

Given the arguments that a bankruptcy event may be considered an uncontrollable external threat, and that firms may respond to an uncontrollable external threat in a conservative way, I propose that when a bankruptcy event occurs, competitors may reduce their investment into innovation activities. Innovation is critical for firms to survive (Schumpeter, 1942); further, innovation is often valuable, rare and inimitable (Barney, 1991), thereby, becoming the source of competitive advantage (Porter, 1992). However, innovation is risky and requires significant firm commitment while its outcomes are uncertain (Griliches, 1990; Hall, Jaffe, and Trajtenberg, 2005). Research has shown that environmental conditions often strongly influence firms' investment into innovation activities as well as firms' risk-taking through innovation activities (e.g., March, 1991). In particular, environmental turbulence may pose a common threat to firms in the same industry, thereby, leading to similar patterns of innovation search and of commitment to innovation activities (Chen and Miller, 2007; Gort and Wall, 1986; Patel and Pavitt, 1997). Thus, competitors upon a bankruptcy event may show similar patterns of innovation search and investment in innovation activities.

Threat-rigidity theory suggests that the goal of organizations faced with an external threat is to reduce potential losses while conserving existing resources (Hartman and Nelson, 1996; Mittal and Ross, 1998). Because a bankruptcy occurs when a company cannot meet its debt obligations, competitors may focus on cutting their own costs as a way to prevent any potential problems. Thus, competitors may reduce investment into innovation activities which is risky and requires significant capital expenditure (Griliches, 1990; Hall *et al.*, 2005). In spite of such risks and challenges inherent in R&D investment, the outputs from these activities are at best uncertain in terms of their technological and market value (Aghion and Tirole, 1994; Griliches, 1998; Hall *et al.*, 2005; Holmstrom, 1989; Miller and Friesen, 1982). In other words, a higher level of R&D investment may make firms vulnerable to market and technological uncertainties (Miller and Friesen, 1982). Specifically, the value of the R&D investment outcome (i.e., products or process innovations) depends on whether customers will be satisfied with the innovation in the future and how competitors' products or actions affect the value of the focal firm's innovations (Miller and Dröge, 1986). Further, it is highly uncertain that R&D investment would result in the successful development of new products or processes in the first place (Miller and Bromiley, 1990). Even when compared with other investment, the risk of R&D investment is clear; for instance, advertising expenditure for existing products or expanding production lines for existing products may generate predictable outcomes than R&D investment (Czarnitzki and Kraft, 2009). In addition to the high risks of R&D investment, it is well known that R&D investment consumes considerable resources (Griliches, 1990; Hall *et al.*, 2005). In particular, prior empirical studies show that R&D investment to create new products is more expensive and requires a significant increase in firm R&D spending (Clark, Chew, Fujimoto, Meyer, and Scherer, 1987; Dyer, 1996; Harryson, Dudkowski, and Stern, 2008; Mudambi and Swift, 2014). Therefore, in the face of the external threat of bankruptcy, competitors that try to conserve existing resources are less likely to invest in innovation activities.

To summarize, R&D investment is highly risky due to market and technological uncertainties and it requires considerable resources. Therefore, competitors that seek to reduce losses and to conserve existing resources in the face of the threat from a bankruptcy event may decrease investment in innovation activities.

Hypothesis 1a: Bankruptcy events negatively affect competitors' investment into innovation activities. That is, competitors' investment in innovation activities will decrease in the post-bankruptcy period.

I also argue that competitors' innovation may decrease upon bankruptcy event. Threat-rigidity theory suggests that in the face of an external threat firms may focus on improving short-term efficiency and reduce information processing. Competitors of bankrupt firms are, therefore, more likely to perfect their existing routines in order to lower costs and generate predictable, reliable outcomes in the short-term; while they avoid non-routine activities which generate unpredictable outcomes particularly in the short-term (Levitt and March, 1988; Nelson and Winter, 1982). Prior research suggests that long-term orientation is critical in innovation activities (Azoulay, Graff Zivin, and Manso, 2011; Cheng, 2004) and innovative firms often forgo short-term returns in the hope of future returns (Aghion and Tirole, 1994). Indeed, empirical studies show that with long-term incentives firms create more innovations (Aghion, Van Reenen, and Zingales, 2013; Lerner and Wulf, 2007). Thus, in the face of the external threat from bankruptcy event, competitors that are incentivized to increase short-term efficiency may create less innovations.

Further, upon bankruptcy competitors may try to minimize information processing, for instance, by refining standardized operating procedures which can be executable with existing information in the organization (Staw *et al.*, 1981). Because integration of new ideas into the organization is critical for developing new innovations (Zhou and Wu, 2010), competitors' emphasis on incremental improvement of existing operations and avoiding new information processing may also decrease innovations of competitors. In other words, competitors' focus on refinement of existing routines and avoidance of new information processing may lower the chance that the competitors can come up with new ideas, which in turn may develop into new innovations. Therefore, I hypothesize:

Hypothesis 1b: Bankruptcy events negatively affect competitors' innovations. That is, competitors' innovation will decrease in the post-bankruptcy period.

2.2.3. Threat-rigidity theory and competitors' technology breadth and generality

While, as hypothesized above, I believe that bankruptcy event will decrease competitors' commitment to innovation activities, I also argue that the rigid response to the threat from an industry bankruptcy will also affect *how* competitors conduct innovation activities. Because how to conduct innovation activities may affect the returns to innovation activities (Cabral, 2003; Henderson, 1993; March, 1991), the choice of how to conduct innovation activities may be an important decision for competitors upon bankruptcy. For instance, if a firm conducts innovation activities in narrower areas with which the firm is familiar (i.e., local search), the returns to innovation activities may be more predictable and stable in the short-term (March, 1991). In contrast, if a firm conducts innovation activities in diverse areas or integrate totally new knowledge to the firm in innovation activities (i.e., distant search), the returns to innovation activities may be uncertain and realizing the returns may take longer time than local search (March, 1991). However, such explorative and experimental innovation activities may generate innovation with broad technological scope – that is, the innovation that is useful in diverse areas (Sorenson, McEvily, Ren, and Roy, 2006).

I argue that competitors of the bankrupt firm may conduct innovation activities in more narrow areas upon bankruptcy, thereby, generating stable returns in the short-term from innovations with specific applications. As aforementioned, the rigid responses to an external threat may lead to the processing of information that confirms past experience and existing knowledge and leads to an organizational emphasis on efficiency and conservation of resources (Ocasio, 1995; Staw *et al.*, 1981). Thus, in the post-bankruptcy period, inventors and scientists of competitor firms are more likely to refine existing innovations and utilize knowledge with which they are already familiar; by doing so, competitors may spend fewer resources while enjoying increasing returns to knowledge and experience in those areas (Levinthal and March, 1981; March, 1991). However, technology breadth of the competitors will become narrower as they conduct innovation activities in the areas with which they are already familiar.

Although refinement of existing innovations may lead to increasing returns, the consequent narrower knowledge breadth may take away opportunities for creating innovations that combine knowledge from diverse areas (Patel and Pavitt, 1997). Innovation activities with knowledge from diverse areas are more likely to generate general purpose innovations, while innovation activities in narrow areas may generate innovations with specific applications (Sorenson *et al.*, 2006; Toh, 2014). However, the outcomes of innovation activities with knowledge from diverse areas are less reliable (Martin and Mitchell, 1998) due to the greater cognitive effort and different know-how required for such innovation activities (Grant, 1999). Because competitors of the bankrupt firm may focus on short-term efficiency upon bankruptcy, they may be less willing to utilize knowledge from diverse areas in their innovation activities and, consequently, they are more likely to generate innovations with specific applications (i.e., narrower technology generality) rather than innovations useful in diverse areas.

To summarize, the external threat of bankruptcy may change how competitors conduct innovation activities. Competitors may conduct innovation activities in narrower areas where the returns are more reliable in the short-term; consequently, competitors are more likely to create innovations useful in specific areas rather than useful in broader areas. Thus, competitors' technology breadth and technology generality may decrease in the post-bankruptcy period. Following is my hypothesis:

Hypothesis 2: Bankruptcy events negatively affect competitors' (a) technology breadth, and (b) technology generality. That is, competitors' (a) technology breadth will be narrower and (b) competitors' technology generality will be lower in the post-bankruptcy period.

In the main hypotheses, I suggest that the external threat represented by a bankruptcy event may decrease innovation activities as well as change the way they conduct innovation activities. To further substantiate the underlying logic of my main hypotheses, I examine how competitors' behavioral changes in innovation activities caused by a bankruptcy event depend on each competitor's own bankruptcy risks. Examining the moderating effect of competitors' own bankruptcy risks may also help us test the consistency of my logic behind main hypotheses, that is, help us examine whether my main logic of contagion effect in main hypotheses (rather than competitive effect) are correct.

2.2.4. Bankruptcy events and competitor's own bankruptcy risks

The degree to which a firm changes its behaviors in response to external threat often depends on the firm's own situation (Ocasio, 1997; Scott, 1992) such as performance aspiration, bankruptcy risk, and slack (e.g., Chen and Miller, 2007; Greve, 2003; March and Shapira, 1987). In particular, prior studies show that a firm's own bankruptcy risk may lead to strong threat-rigid responses such as the decrease in innovation search intensity (Chen and Miller, 2007), business scope and strategic initiatives (D'Aveni 1989), and competitive actions (Ferrier et al. 2002).

Given the argument that the degree to which competitors perceive a threat from industry bankruptcy may depend on their own situations (Ocasio, 1997; Scott, 1992), I posit that a competitor's own bankruptcy risk may affect the extent to which the competitor perceives a strong threat from industry bankruptcy. If a competitor is in a similar situation with the focal bankrupt firm, then the extent to which bankruptcy event threatens the competitor may be stronger; in contrast, if a competitor is in a different situation, the threat from bankruptcy may affect the competitors to a lesser degree. Thus, I propose that when a competitor's own bankruptcy risk is higher, competitor firm may perceive a stronger threat from industry bankruptcy because the likelihood that they fall into the same situation is higher than others, thereby, creating a greater damage-control mindset and psychological stress and anxiety for organization (Audia and Greve, 2006). Consequently, their threat-rigid responses will be stronger than firms with lower bankruptcy risks. Specifically, competitors with higher bankruptcy risks may further restrict information processing, conserve existing resources to increase efficiency, and rely more heavily on organizational activities over which they have greater control. This may, in turn, lead competitors to decrease commitment to innovation activities and to conduct innovation activities in even more conservative ways.

To summarize, competitors in a similar situation with the bankrupt firm (i.e., with greater own bankruptcy risks) may perceive industry bankruptcy as a stronger threat. As a result, those competitors are more likely to respond to the threats of bankruptcy with stronger internally-directed behaviors (Chattopadhyay *et al.*, 2001; Ocasio, 1995; Staw *et al.*, 1981), thereby, leading to a larger decrease in innovation activities and to the execution of innovation activities in more conservative ways. Thus, I advance the following hypothesis:

Hypothesis 3: Competitors' own bankruptcy risks moderate the relationship between bankruptcy events and (a) competitors' investment into innovation activities, (b) innovation, (c) technology breadth, and (d) technology generality, such that when competitors' own bankruptcy risk is higher, the negative effect of bankruptcy on competitors' (a) investment into innovation activities, (b) innovation, (c) technology breadth, and (d) technology generality are more pronounced.

2.3. DATA AND METHODOLOGY

2.3.1. Sample

I formed my sample from the intersection of (1) the UCLA-LoPucki Bankruptcy Research Database (BRD), (2) the Hoberg-Phillips Text-based Network Industry Classification (TNIC), (3) the U.S. Patents database by Kogan, Papanikolaou, Seru, and Stoffman (2017) and the USPTO PatentsView database, and (4) Standard and Poor's Compustat.

I first identified bankrupt firms from the UCLA-LoPucki Bankruptcy Research Database (BRD). The entire universe of BRD is bankrupt firms of which (1) reported assets are larger than 100 million U.S. Dollars (USD) in dollar values from 1980 (greater than 280 million current USD) and (2) annual reports are filed within three years before the bankruptcy filing. Thus, the bankrupt firms in the BRD represent bankruptcy cases of large public firms. There are 965 bankrupt firms between 1980 and 2012 in the BRD. Following prior studies (Akhigbe *et al.*, 2005; Ferris *et al.*, 1997; Lang and Stulz, 1992), I use 945 Chapter 11 bankruptcy filings in my study.

After identifying bankrupt firms, I needed to identify competitors of bankrupt firms. Defining product competitors of bankrupt firms is crucial to my empirical investigation.

Following prior competitor studies that also employ difference-in-differences approach (Ammann, Horsch, and Oesch, 2016; Shi, Zhang, and Hoskisson, 2017), I used the Hoberg-Phillips Text-based Network Industry Classification (TNIC) to identify bankrupt firms' product competitors (Hoberg and Phillips, 2016). TNIC measures pairwise product similarity and identifies competitiveness between a pair of public firms. Specifically, the pairwise product similarity is calculated by the common words ratio in the business description section in firms' 10K filings. Because Securities and Exchange Commission (SEC) regulations require firms to report their significant products offered to their customers, public firms describe their product details in the business description section of 10K filings (Hoberg and Phillips, 2016). Following Hoberg and Phillips (2016), I use the 21.32% minimum similarity threshold to define competitors. That is, a pair of firms that have a common words ratio of 21.32% or above is defined as competitors. Another notable characteristic of the TNIC classification is non-transitivity. The TNIC classifies a pair of firms as competitors only when the pair of firms have larger than 21.32% similarity. For example, if firm A and B are 30% similar, they are classified as competitors. Now consider firm C that is 25% similar to firm B and that is 15% similar to firm A. Here, firm C is a competitor of firm B but not a competitor of firm A. Thus, even though firm A is a competitor of firm B and firm B is a competitor of firm C, firm A and firm C are not a competitor to each other due to the non-transitivity character of the TNIC classification. Consequently, each firm has its own distinct set of competitors that are focal-firm centric competitors. In contrast, transitivity occurs using the Standard Industry Classification (SIC). That is, the SIC classifies all firms in an industry as competitors. Thus, if firm A is a competitor of firm B (30% similarity) and if firm B is a competitor of firm C (25% similarity), as in my example, then firm A and C are automatically competitors based on SIC classification even though firm A and firm C have lower similarity (15% in my example).

I use only the data of bankrupt firms that filed annual reports in the year of bankruptcy or one year prior to bankruptcy in order to accurately identify their competitors. There are 418 bankrupt firms between 1980 and 2012 that meet this criterion. Among these firms, I further limit my bankrupt-firm sample to 317 bankrupt firms between 1996 and 2007 because I need a 7-year window for my dependent variables (i.e., competitors' innovation activities, search breadth, technology breadth and hits and misses) and there are time period limitations for the TNIC and Kogan et al.'s (2017) Patent databases. For instance, consider Polaroid Corp. that filed bankruptcy in 2001; I match Polaroid Corp. with its competitors using TNIC data. Then, to employ the DiD approach, I observe the competitors' innovation over seven years including three years before Polaroid's bankruptcy (1998 - 2000), the year of bankruptcy (2001) and three years subsequent to bankruptcy (2002 - 2004). Because TNIC pairwise product similarity data is available from 1996 which I use for sample matching, I include bankrupt firms from 1996. Likewise, Kogan et al.'s (2017) patent database provides firms' patent information up to 2010. Thus, I include bankrupt firms up to 2007, which allows for 7-year windows (2004 - 2010) for the observations of matched competitors. The selection of a short window of time may minimize bias caused by environmental changes, which in turn, helps us more accurately capture the impact of bankruptcy events on competitors' innovation.

Based on TNIC data, I match bankrupt firms between 1996 and 2007. During the matching process, I found that some firms had been competitors of multiple bankrupt firms in the BRD database. Consistent with prior study, in such cases, I focus on the first bankruptcy event experienced by the competitors (Shi *et al.*, 2017). Then, I merge the competitors with Kogan et al.'s (2017) U.S. Patents database using firm identifiers (i.e., PERMNO). Kogan et al. (2017) created the U.S. Patents database, which provides patent information from 1926 to 2010 with associated firm identifiers. This database is comparable to the NBER Patent database in terms of assignee matching accuracy and this database has been used by management and economics scholars (e.g., Choi and McNamara 2017, Kogan et al. 2017). I obtain the information about patent classification from the PatentsView database since Kogan et al. (2017)'s Patent database provides limited information about each patent. PatentsView was created by the US Patent and Trademark Office (USPTO) and this database provides U.S. patent information up to December 26, 2017.

In order to control for omitted variables, industry effects, and other factors that may affect competitors' innovation, I use a difference-in-differences approach. In order to conduct difference-in-differences regressions, I identified control firms using propensity score matching. First, I required that control firms have never been competitors of any bankrupt firms. Second, to identify the closest neighbor of each rival firm, I conducted logit regression with independent variables including firm size, firm profitability, number of patents, R&D, industry sales growth, industry sales turbulence, and industry fixed effects (SIC 2 digit) with the competitor dummy as the dependent variable. Firm characteristic variables may help us match competitors with similar firms in the control group pool. In the matching process, I also used industry characters such as industry sales growth and industry sales turbulence with industry fixed effects (SIC 2 digit) because doing so may minimize bias driven by environmental characteristics. For instance, economic turbulence faced by the industry at large may decrease/increase firm innovations in the industry in different ways from the bankruptcy event (Benmelech and Bergman, 2011). Further, lower industry sales growth may increase the likelihood that firms in the industry file for bankruptcy. In such cases, both the competitors' innovation and bankruptcy in the industry may be affected by environmental conditions in the industry at large. The variables used in the matching process are calculated in the same fashion as the same variables in the Control variables section are calculated. All variables used for the logit regression are measured at t – 1 (i.e., one year before the bankruptcy) and strictly before the bankruptcy event. Thus, among the control group pool, I chose the firms most similar to competitors and those experiencing industry conditions under which a bankruptcy event is likely but did not actually occur. Following prior studies (Bloom, Schankerman, and Van Reenen, 2013; Gao and Zhang, 2016), I further exclude the pairs of competitor and control firms that have never filed for any patents during the entire sample period. Also, I exclude firm-year observations for which necessary accounting variables are missing from Compustat. These selection criteria yielded a sample of 1,900 pairs of competitor and control firms and of 20,193 firm-year observations from 236 bankruptcy cases.

2.3.2. Dependent variables: innovation variables

I constructed investment in innovation activities and patent-based metrics for competitors' innovation (Hall *et al.*, 2005; Hall, Jaffe, and Trajtenberg, 2001) as follows. For investment in innovation activities, I use industry adjusted R&D – operationalized as firm R&D minus industry median R&D (SIC 2 digit) as a proxy for investment into innovation activities (Cho and Kim, 2017). I use as a proxy for innovation the number of patent applications that were filed by a firm in a year and that have been eventually granted. Patent applications are presumably closer to actual innovations given that it takes two years on average for a patent to be granted (Hall *et al.*, 2001). However, because of this lag, the number of patents may decrease in the last few years of my sample. To correct for this truncation issue I included year fixed effects in my regressions consistent with prior studies (e.g., Flammer and Kacperczyk, 2015; Hall *et al.*, 2005). Due to the skewness of the variable, I used the natural logarithm of one plus the number of patents (i.e., Ln(1 + patents)). I set innovation to zero in cases where a firm had no patent. This approach reduces sample selection bias (Atanassov, 2013) and has been commonly used in prior literature (e.g., Flammer and Kacperczyk, 2015; Tian and Wang, 2011).

I further constructed technology breadth, which is defined as one minus the Herfindahl Hirschman index of patent classes of a firm's patents in a year. Specifically, I operationalize technology breadth as follows:

$$\text{Technology breadth } = 1 - \sum_{i=1}^{n} P_i^2,$$

where p_i is the share of patents in USPTO patent class i over the total number of patents of a firm in all USPTO patent classes. The higher the value for this variable, the broader the technology breadth of the focal firm.

I further constructed the technology generality variable in a similar fashion as technology breadth. Instead of patent classes of a firm, I used patent classes of citations made to the focal firm's patents to calculate this variable. This measure is the same as the measure of generality developed by Trajtenberg, Henderson, and Jaffe (1997) but one minor difference is that I calculate this measure at the firm level rather than patent level (Kim, Arthurs, Sahaym, and Cullen, 2013). Specifically, I operationalize technology generality as follows:

$$\text{Technology generality } = 1 - \sum_{i=1}^{n} P_i^2,$$

where p_i is the share of patent citations made to a firm in USPTO patent class i over the total number of patent citations made to a firm in all USPTO patent classes. Thus, this variable represents the extent to which a focal firm's patents are cited by various technologies. A higher value for this variable indicates that a firm's patents are cited by patents in diverse technology classes and this shows that the firm has general-purpose technologies rather than technologies with specific applications.

2.3.3. Moderating variable

As a proxy for bankruptcy risk, I used a reverse coded Altman's Z score (i.e., $-1 \times$ Altman Z) (1983). I operationalized Altman-Z as (1.2 × working capital divided by total assets) + (1.4 × retained earnings divided by total assets) + (3.3 × earnings before interest expense and taxes divided by total assets) + (0.6 × equity divided by debt) + (0.999 × sales divided by total assets). Because I reverse coded Altman's Z score, the higher value of this variable indicates that there is a higher likelihood that the firm goes bankrupt. I also include this variable as a control variable in regression analyses to control for the firm-specific threat. As shown in prior studies (Chen and Miller, 2007; D'Aveni 1989; Ferrier et al. 2002), bankruptcy risk is a threat to the focal firm and leads to threat-rigid responses.

2.3.4. Control variables

I controlled for firm characteristics and industry characteristics that may influence firm innovation. Specifically, I controlled for firm characteristics including firm size, firm profitability, leverage, cash holdings, and R&D intensity. I controlled for industry characteristics including sales turbulence, industry sales growth, and industry concentration. I also controlled bankruptcy characteristics including prepackaged bankruptcy and voluntary bankruptcy. All control variables except for bankruptcy characteristics were lagged by one year.

I operationalized firm performance as earnings net income scaled by sales (ROS). Prior studies show that a firm's search behavior and search intensity changes depending on its financial performance (Greve 2003). I operationalized leverage as long-term debt scaled by total assets. Higher leverage may lower the flexibility of firms in choosing future strategies (Greve 2003) while lower leverage represents higher resource slack and this may increase explorative search (Ahuja, Lampert, and Novelli, 2013). I operationalized R&D as R&D expenditure scaled by total assets. R&D expenditure is input to firms' innovation activities. Further, R&D is a good proxy for the absorptive capacity of a firm, which represents the extent to which a firm assimilates external knowledge and generates innovations (Cohen and Levinthal 1990). I set R&D to zero if R&D expenditure is missing in COMPUSTAT following prior studies (Bansal, Joseph, Ma, and Wintoki, 2016). Because the Securities and Exchange Commission requires public firms to report any material R&D expenditure, missing R&D expenditure reveals that the firm has no R&D expenditure or little R&D expenditure in the year (Bansal *et al.*, 2016).

I also control for industry characteristics including industry sales turbulence, industry sales growth, and industry concentration. Industry sales turbulence (Uotila, Maula, Keil, and Zahra, 2009) and growth (Klevorick, Levin, Nelson, and Winter, 1995) may affect the effectiveness of firm innovations and firm innovation search. Following prior studies (Dess and

Beard, 1984; Karim, Carroll, and Long, 2016), I operationalize industry sales growth and turbulence as followings:

$$y = b_0 + b_1 t + a_t$$

I regress industry sales (2-digit SIC) on time (the past five years). Industry growth is the time coefficient estimate (β_1) scaled by the mean of the industry sales for the past five years and industry turbulence is the standard error of the time coefficient estimate (β_1) scaled by the mean of the industry sales for the past five years. I operationalize industry concentration as the Herfindahl Hirschman index of sales in the 2-digit SIC industry. Schumpeter (1942) argues that, in highly concentrated industries, large firms have more incentives to pursue innovation.

Finally, I control for year-fixed effects and for firm-fixed effects in my OLS regressions. It is worth noting that I control for firm time-invariant effects because competitors' time-invariant characters (e.g., competitiveness and innovation routines) might affect the firm's innovation activities.

2.3.5. Method

I ran ordinary least squares (OLS) regressions to conduct the DiD analysis. Specifically, I estimated the following regression:

$$y_{i,t} = \alpha_i + \alpha_t + \beta_1 \textit{competitors in post BR period}_{it} + \gamma \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t}$$

where *i* indexes firm and *t* indexes year. *Competitors in post bankruptcy (BR) period* is a dummy variable. *Competitors in post BR period* is coded "1" if a firm is the competitor of the bankrupt firm in the post-bankruptcy firm-year and "0" otherwise. That is, competitors receive a value of 1 only if the observation is in firm-year after bankruptcy and receive a value of 0 if the observation is in firm-year before bankruptcy; control firms always receive a value of 0. The *Competitors in post BR period* is the primary variable of interest (i.e., the independent variable of my study). Thus, the coefficient of interest is β_1, which measures the effect of the bankruptcy event on competitors' innovation. Hypotheses 1 and 2 predict that the coefficient β_3 should be negative. α_t is year fixed effects and α_i is firm fixed effects. $\boldsymbol{X}$ is the vector of control variables and all control variables in my study except for bankruptcy characteristics are lagged by one year. ε is the error term.

2.3.6. Results

Table 2.1 reports descriptive statistics for the matched sample of 1,900 pairs of competitor and control firms. In order to check the balance of the sample, I conducted t-test and the results show that the means of these variables are not significantly different. That is, the statistics suggest that there is no difference in firm characteristics between a group of competitors and control firms in the pre-bankruptcy period. Table 2.2 provides descriptive statistics for the variables and pairwise correlations between the variables I use in my main analyses.

Our main results are reported in Table 2.3. The coefficient estimate for *Competitors in post BR period* is negative but insignificant in Model 1 ($\beta = -0.01$, $p = 0.624$). Thus, Hypothesis 1(a) is not supported. In Model 2, The coefficient estimate for *Competitors in post BR period* is negative and significant ($\beta = -0.09$, $p = 0.000$), supporting Hypothesis 1(b). The coefficient estimate of -0.09 indicates that competitors' innovation decreases (i.e., number of patents) by 9% following the bankruptcy event. The coefficient estimate for *Competitors in post BR period* in Model 3 ($\beta = -0.01$, $p = 0.151$) is negative but insignificant; thus, Hypothesis 2(a) is not supported. However, the coefficient estimate for *Competitors in post BR period* in Model 4 ($\beta = -0.02$, $p = 0.035$) is negative, supporting Hypothesis 2(b). Overall, these findings show that competitors' innovation decreases and technology breadth become narrower; while firm R&D and technology remain similar in the post-bankruptcy period.

To test the moderating effects of competitors' own bankruptcy risk proposed in Hypothesis 3, I included the interaction of *Competitors in post BR period* × *Bankruptcy risk* into my regression, following prior studies (Wang, Zhao, and He, 2015; Younge, Tong, and Fleming, 2015). my interaction effects results are reported in Table 2.4. The coefficient estimate for *Competitors in post BR period* × *Bankruptcy risk* is negative in Model 1 ($\beta = -0.02$, $p = 0.000$), supporting Hypothesis 3(a). The coefficient estimate for *Competitors in post BR period* × *Bankruptcy risk* is negative in Model 2 ($\beta = -0.01$, $p = 0.005$), supporting Hypothesis 3(b). Thus, competitors with higher own bankruptcy risks decrease investment into R&D and suffer from lower innovation in the post-bankruptcy period. The coefficient estimate for *Competitors in post BR period* × *Bankruptcy risk* is negative in Model 3 ($\beta = -0.00$, $p = 0.038$), supporting Hypothesis 3(c). The coefficient estimate for *Competitors in post BR period* × *Bankruptcy risk* is also negative in Model 4 ($\beta = 0.01$, $p = 0.009$) supporting Hypothesis 3(d). Thus, competitors with higher own bankruptcy risk reduce technology breadth and, consequently, their technology generality decreases in the post-bankruptcy period. In sum, these findings show that competitors with higher own bankruptcy reduce investment into innovation activities and they also conduct innovations in more conservative ways in the post-bankruptcy period. my findings suggest that the behavioral changes of competitors in innovation activities become stronger when each competitor's own bankruptcy risks are higher.

2.3.7. Robustness check

I conceptualized that industry bankruptcy creates a dominant contagion effect on competitors. In order to justify that competitors' change in innovation activities are driven by the contagion effects of bankruptcy rather than competitive effect, I conducted additional analyses. Since a bankruptcy announcement may convey negative information about the bankrupt firm as well as competitors (Akhigbe et al., 2005; Ferris et al., 1997; Hertzel et al., 2008; Jorion and Zhang, 2007; Lang and Stulz, 1992), the market may adjust downward its expectation of competitors' future competitiveness in the industry. Given the argument, competitors' announcement returns and financial performance are likely to decline in the post-bankruptcy period. I conducted event study using WRDS Event Study database and, as shown in Table 2.5, compared with control firms' cumulative abnormal returns (CARs), competitors' CARs decline upon bankruptcy events across different event windows (-3/+3, -5/+5, -10/+10 and -30/+30). The coefficient estimate for *Competitors in post BR period* is negative in all models including Model 1 ($\beta = -0.01$, $p = 0.058$), Model 2 ($\beta = -0.02$, $p = 0.022$), Model 3 ($\beta = -0.03$, $p = 0.014$) and Model 4 ($\beta = -0.07$, $p = 0.000$) and these findings confirm prior findings that bankruptcy events create negative externalities to competitors. As shown in Model 5, competitors realize poor operating performance (ROA) in the post-bankruptcy period ($\beta = -0.04$, $p = 0.008$), confirming that competitors suffer from negative externalities of bankruptcy event.

2.4. DISCUSSION

In this study, I examine how bankruptcy influences competitors' behaviors in the context of innovation. I then explore how the effects of the bankruptcy on competitors' innovation depend upon the competitors' own bankruptcy risks. I explore these interrelationships because bankruptcy events create negative externalities and pose external threats to competitors, which may, in turn, influence their innovation in the post-bankruptcy period.

By employing a difference-in-differences approach, I find that competitors' innovation - measured as the number of patents – decreases. I also find that competitors conduct innovation activities in a conservative way – measured by decreases in technology breadth – in the post-bankruptcy period, while competitors' R&D and technology generality remain similar in the post-bankruptcy period. However, competitors' R&D, innovation, technology breadth and technology generality all decrease in the post-bankruptcy period when competitors' own bankruptcy risk is higher. In sum, my study suggests that a bankruptcy event poses an external threat and competitors become rigid in the post-bankruptcy period; such external threat is stronger for firms with higher own bankruptcy risks, thereby, leading to stronger threat-rigid responses.

2.4.1. Contributions to the literature on bankruptcy

This study contributes to the bankruptcy literature by shedding light on how bankruptcy events affect the way competitors change their behaviors in the post-bankruptcy period. Previous research has examined and emphasized the contagion effect of bankruptcy on competitors. The contagion effect spreads to industry peers and leads to a loss in market value, a decline in market demand and weakening prospects for the future (Akhigbe et al. 2005, Lang and Stulz 1992). Further, a bankruptcy increases the competitors' credit default swap spreads (Jorion and Zhang 2007) and costs of debt financing due to bankruptcy's negative effect on competitors' collateral value (Benmelech and Bergman 2011). While extant research has examined how external stakeholders respond to bankruptcy events, my study shows that bankruptcy events induce competitors to change their innovation behavior in the post-bankruptcy period. Consistent with threat-rigidity theory, I find that bankruptcy events reduce competitors' innovation activities and lead competitors to conduct innovation activities in conservative ways, particularly when competitors have higher own bankruptcy risks. Thus, my study shows that competitors change their behaviors in the post-bankruptcy period. They respond to a bankruptcy event in an industry by decreasing innovation activities because they are threatened by bankruptcy events. Accordingly, my study supports the contagion effect and disconfirms the competitive effect.

2.4.2. Contributions to the literature on threat-rigidity theory

Threat-rigidity theory suggests that organizations in the face of a threat become risk-averse and exhibit rigid responses (Chattopadhyay et al. 2001, Ocasio 1995, Staw et al. 1981). In prior literature, scholars have mainly focused on the effects of a direct, firm-specific threat on firm behaviors. For example, firms with their own bankruptcy risks reduce innovation search intensity (Chen and Miller, 2007), narrow business scope (D'Aveni 1989), and reduce competitive actions (Ferrier et al. 2002). Moreover, when firms underperform relative to aspirations, they decrease strategic change (McDonald and Westphal 2003), divest poor performing units (Hayward and Shimizu 2006, Shimizu 2007), lower acquisition activity (Iyer and Miller 2008), and reduce costs (Schendel et al. 1976, Starbuck 1992). One notable exception is the study by Beckman, Haunschild, and Phillips (2004) that showed that market uncertainty (operationalized as stock price volatility of industry) as an external threat to all firms is associated with higher alliances with existing alliance partners rather than with new alliance partners. Extending the literature, my study shows how and why bankruptcy events of industry peers – external events caused by a third-party – pose a significant threat to competitors and in turn reduce competitors' innovation activities. Further, my study also shows that an external threat, when combined with a firm-specific threat (i.e., a competitor's own bankruptcy risks), leads to stronger threat-rigid response. To the best of my knowledge, the threat-rigidity literature has not examined the combined effect of internal and external threats on behavioral change in organizations. Thus, my results provide new insights into threat-rigidity literature.

2.4.3. Contributions to the literature on innovation

Our study also contributes to innovation research by showing how industry conditions affect innovation activities. Schumpeter (1939) suggests that innovation activities may increase during economic downturns due to lower opportunity costs associated with those periods. However, scholars have found that innovation activities are procyclical (Fabrizio and Tsolmon, 2014; Griliches, 1990). This literature suggests that not only long-term industry growth affects innovation activities of industry firms (Fabrizio and Tsolmon, 2014; Griliches, 1990) but also short-term demand shock decreases innovation activities in an industry (Ouyang, 2011). I extend these studies by demonstrating that negative externalities of bankruptcy as a short-term shock lowers innovation activities of industry competitors. Consistent with prior studies (Fabrizio and

Tsolmon, 2014; Griliches, 1990; Ouyang, 2011), liquidity constraints, which are caused by the increasing costs of debt financing upon bankruptcy (Benmelech and Bergman, 2011), may be one of the driving forces that decrease industry competitors' innovation activities in the post-bankruptcy period. Further, my findings show that firms show similar patterns of innovation activities and search behaviors in the face of a common threat (Chen and Miller, 2007; Gort and Wall, 1986; Patel and Pavitt, 1997).

2.4.4. Limitations and future research

This study is not without limitations. my study conceptualizes bankruptcy events as an external threat. A limitation of this conceptualization is that it does not directly measure competitors' perception about bankruptcy events. Thus, it might be fruitful to survey managers of competitors and measure the extent to which bankruptcy events influence the perceived threat. To generalize my findings, it might be beneficial to investigate the effects of bankruptcy events on competitors in a variety of contexts. If bankruptcy of industry peers induces competitors to become rigid, competitors are less likely to engage in corporate activities that entail higher risk. For example, I speculate that competitors may reduce the number of acquisitions in which they engage in the post-bankruptcy period. Future studies could also examine which firms benefit from bankruptcy events. Although most studies show that bankruptcy events generate a dominant contagion effect, financial distress might enable some firms to actually develop disruptive innovations or products or initiate new technological trajectories which reshape the post-bankruptcy industry. Finally, it would be interesting to examine the top management teams of the firms to identify what team characteristics affect the magnitude of the rigidity response. There may be some team characteristics which help firms avoid the rigid response after a bankruptcy in the industry. I look forward to examining these issues in the future.

Table 2.1. Descriptive Statistics of Competitors and Matched Non-Competitors

Each control firm is the closest neighbor of competitors among all public firms that are available in COMPUSTAT in the same year and that have never been rivals of bankrupt firms. T-test results indicate that there is no significant difference in means between competitors and matched non-competitors. Variables are constructed in the same way as control variables used in main analyses.

	Competitors (T)			Control firms (C)			Difference in means
Variables	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	*p*(T-C)
Firm size	1,900	5.152	2.275	1,900	5.272	2.809	0.149
R&D intensity	1,900	0.091	0.139	1,900	0.083	0.151	0.094
Firm profitability	1,900	-1.544	5.605	1,900	-1.511	6.167	0.864
Innovation	1,900	0.931	1.319	1,900	0.911	1.668	0.691
Industry growth	1,900	0.091	0.052	1,900	0.093	0.052	0.171
Industry turbulence	1,900	0.015	0.012	1,900	0.015	0.012	0.180

Table 2.2. Pairwise Correlations and Descriptive Statistics

All correlations with an absolute value equal to or greater than 0.03 are statistically significant at P < 0.05. [a] Variables winsorized at 1% and 99% in each year to eliminate outliers; firm profitability variable is winsorized at 5% and 99% due to its skewness. I conducted all regression analyses in my study with this variable winsorized at 1% and 99%, 3% and 99%, and 5% and 99%, respectively, and the results were similar.

	Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	Innovation	1.00											
2.	Technology generality	0.51	1.00										
3.	Technology breadth	0.74	0.61	1.00									
4.	Industry adj. R&D	0.69	0.36	0.50	1.00								
5.	Firm size	0.44	0.30	0.48	0.44	1.00							
6.	Firm profitability [a]	0.05	0.10	0.07	0.04	0.26	1.00						
7.	Firm leverage [a]	-0.09	-0.03	0.03	-0.13	0.06	-0.03	1.00					
8.	R&D intensity [a]	0.02	-0.12	-0.13	0.10	-0.49	-0.29	-0.10	1.00				
9.	Industry growth	-0.13	0.06	-0.09	-0.05	-0.07	0.04	-0.02	-0.04	1.00			
10.	Industry turbulence [a]	-0.06	-0.02	0.00	-0.07	0.04	0.05	0.04	-0.15	0.07	1.00		
11.	Industry concentration	-0.13	-0.05	-0.09	-0.10	0.00	0.05	0.05	-0.19	0.05	0.36	1.00	
12.	Competitors in post BR period	-0.03	-0.12	-0.08	0.00	0.03	-0.03	-0.02	0.03	-0.10	0.06	0.00	1.00
	Mean	1.03	0.72	0.49	1.17	5.21	-1.44	0.24	0.09	0.08	0.02	0.05	0.31
	Standard Deviation	1.60	0.21	0.35	1.81	2.57	9.47	0.30	0.14	0.05	0.01	0.05	0.46

Table 2.3. The Impact of Bankruptcy (BR) on Competitors' Innovation

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by the pair of competitor and control firms; P-values are reported in parentheses; Number of observations for Model 3 – 4 are smaller because only the firm-year observations with at least one patent are used in these columns.

	Model 1	Model 2	Model 3	Model 4
Variables	Industry Adj. R&D	Innovation	Technology breadth	Technology generality
Competitors in post BR period	-0.01	-0.09***	-0.02**	-0.01
	(0.624)	(0.000)	(0.035)	(0.151)
	0.02	0.02	0.01	0.01
Firm size	0.22***	0.11***	0.02**	0.00
	(0.000)	(0.000)	(0.024)	(0.515)
	0.01	0.01	0.01	0.01
Firm profitability	-0.00***	-0.00***	-0.00***	0.00
	(0.001)	(0.004)	(0.009)	(0.554)
	0.00	0.00	0.00	0.00
Firm leverage	-0.12***	-0.03	0.02	-0.02
	(0.002)	(0.248)	(0.521)	(0.282)
	0.04	0.03	0.03	0.02
R&D intensity	-0.16	-0.32***	-0.04	-0.03
	(0.112)	(0.000)	(0.523)	(0.437)
	0.10	0.08	0.06	0.04
Industry growth	-0.24*	-0.02	0.13	0.05
	(0.080)	(0.874)	(0.239)	(0.531)
	0.13	0.14	0.11	0.08
Industry turbulence	1.22**	0.44	-0.39	0.17
	(0.016)	(0.455)	(0.423)	(0.690)
	0.50	0.58	0.49	0.42
Industry concentration	0.55**	-0.87***	-0.37	-0.05
	(0.042)	(0.007)	(0.388)	(0.850)
	0.27	0.32	0.43	0.27
Constant	0.19**	0.50***	0.38***	0.74***
	(0.018)	(0.000)	(0.000)	(0.000)
	0.08	0.07	0.06	0.04
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	19,345	19,345	8,444	8,444
R-squared	0.951	0.915	0.760	0.647

Table 2.4. The Moderating Effect of Bankruptcy (BR) Risk on Competitors' Innovation

Robust standard errors are clustered by the pair of competitor and control firms; P-values are reported in parentheses; Number of observations for Model 2 – 5 are smaller because only the firm-year observations with at least one patent are used in these columns.

Variables	Model 1 Industry Adj. R&D	Model 2 Innovation	Model 3 Technology breadth	Model 4 Technology generality
Competitors in post BR period ×	-0.02***	-0.01***	-0.01***	-0.00**
Bankruptcy risk	(0.000)	(0.005)	(0.009)	(0.038)
	0.00	0.00	0.00	0.00
Bankruptcy risk	-0.02***	-0.01**	0.00	-0.00
	(0.000)	(0.017)	(0.919)	(0.785)
	0.00	0.00	0.00	0.00
Competitors in post BR period	-0.02	-0.10***	-0.04***	-0.02**
	(0.233)	(0.000)	(0.004)	(0.043)
	0.02	0.02	0.01	0.01
Firm size	0.21***	0.10***	0.02**	0.00
	(0.000)	(0.000)	(0.020)	(0.488)
	0.01	0.01	0.01	0.01
Firm profitability	-0.00***	-0.00***	-0.00***	0.00
	(0.000)	(0.002)	(0.005)	(0.641)
	0.00	0.00	0.00	0.00
Firm leverage	-0.01	0.00	0.03	-0.01
	(0.836)	(0.982)	(0.369)	(0.607)
	0.02	0.02	0.03	0.02
R&D intensity	0.42***	-0.13	-0.00	-0.00
	(0.000)	(0.172)	(0.978)	(0.971)
	0.11	0.10	0.07	0.05
Industry growth	-0.28**	-0.03	0.12	0.05
	(0.031)	(0.814)	(0.249)	(0.557)
	0.13	0.14	0.11	0.08
Industry turbulence	1.12**	0.41	-0.42	0.15
	(0.021)	(0.475)	(0.387)	(0.716)
	0.49	0.58	0.49	0.42
Industry concentration	0.48**	-0.90***	-0.38	-0.06
	(0.043)	(0.003)	(0.378)	(0.830)
	0.24	0.31	0.43	0.27
Constant	0.13*	0.48***	0.38***	0.73***
	(0.095)	(0.000)	(0.000)	(0.000)
	0.08	0.07	0.06	0.04
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	19,345	19,345	8,444	8,444
R-squared	0.953	0.915	0.761	0.648

Table 2.5. The Impact of Bankruptcy (BR) on Competitors' Cumulative Abnormal Returns and Return on Assets (ROA)

Robust standard errors are clustered by the pair of competitor and control firms; P-values are reported in parentheses; cumulative abnormal returns variable was obtained from Wharton Research Data Services (WRDS) Event Study database. Because WRDS Event Study database requires a different firm identifier (i.e., PERMNO), the identifier used in the study (i.e., GVKEY) was matched with PERMO using CRSP/COMPUSTAT Merged database to the extent possible but I ended up being with 2,049 observations; Fama-French three-factor model is used to calculate cumulative abnormal returns. ROA was operationalized as net income weighted by total assets.

Variables	Model 1 CAR [-3, 3]	Model 2 CAR [-5, 5]	Model 3 CAR [-10, 10]	Model 4 CAR [-30, 30]	Model 5 ROA
Competitors in post BR period	-0.01*	-0.02**	-0.03**	-0.07***	-0.04***
	(0.058)	(0.022)	(0.014)	(0.000)	(0.008)
	0.01	0.01	0.01	0.02	0.01
Firm size	-0.00	0.00	0.00	0.00	-0.01
	(0.971)	(0.636)	(0.660)	(0.731)	(0.261)
	0.00	0.00	0.00	0.01	0.01
Firm profitability	0.00	0.00	0.00	-0.00	0.00*
	(0.673)	(0.603)	(0.633)	(0.674)	(0.065)
	0.00	0.00	0.00	0.00	0.00
Firm leverage	0.01	-0.01	0.02	-0.04	0.05
	(0.655)	(0.684)	(0.485)	(0.432)	(0.378)
	0.02	0.02	0.03	0.05	0.05
R&D intensity	0.05	0.01	0.06	-0.11	-0.19
	(0.331)	(0.853)	(0.460)	(0.440)	(0.145)
	0.05	0.06	0.09	0.14	0.13
Industry growth	0.00	-0.02	0.26	0.38	-0.47***
	(0.998)	(0.881)	(0.132)	(0.241)	(0.000)
	0.11	0.12	0.17	0.33	0.12
Industry turbulence	-0.87*	-1.04	-0.72	-3.00*	1.56***
	(0.091)	(0.109)	(0.440)	(0.054)	(0.000)
	0.51	0.65	0.93	1.56	0.42
Industry concentration	-0.17	-0.39**	-0.39	0.05	0.16
	(0.371)	(0.045)	(0.155)	(0.916)	(0.589)
	0.19	0.20	0.27	0.46	0.30
Constant	0.12**	0.14*	0.14	0.00	-0.05
	(0.032)	(0.064)	(0.332)	(0.996)	(0.422)
	0.06	0.07	0.14	0.19	0.06
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No
Bankruptcy FE	Yes	Yes	Yes	Yes	No
Observations	2,049	2,049	2,049	2,049	19,298
R-squared	0.166	0.177	0.169	0.181	0.604

3. THE EFFECTIVENESS OF SECRECY AS AN APPROPRIATION MECHANISM: EVIDENCE FROM THE UNIFORM TRADE SECRETS ACT

3.1. INTRODUCTION

For innovative firms, appropriation strategy – the way firms capture value from their inventions – determines whether they are able to gain and sustain competitive advantage (Teece 1986). Indeed, innovative firms often have a strong interest in precluding the spillover of their valuable and rare inventive knowledge to competitors (Barney 1991; Grant 1996). Among primary means by which firms appropriate value from their inventions – trade secrecy, patents, lead time and complementary assets (Ceccagnoli and Rothaermel 2016; Teece 1986) – trade secrecy has been rated as the most effective by R&D managers (Cohen, Nelson and Walsh 2000; National Science Foundations 2008). Moreover, numerous historical examples of successful trade secrets, such as Coca-Cola's formula and Google's search algorithm, exist.

Despite trade secrecy's importance and calls to examine factors that moderate the effectiveness of trade secrecy (James, Leiblein and Lu 2013), there have been surprisingly few empirical studies of when trade secrecy is most effective. Indeed, firms don't always use trade secrecy in isolation; rather, they often concurrently employ trade secrecy with other appropriation mechanisms under varying industry conditions (Hall, Helmers, Rogers and Sena 2014). Prior research has examined the effect of strong trade secret legal protection on changes in firms' inventive efforts (Png 2017a), use of patenting as substitute (Png 2017b), financial policies (Klasa, Ortiz-Molina, Serfling and Srinivasan 2018), and inventors' motive to innovate (Contigiani, Hsu and Barankay 2018). However, the questions of how and when trade secrecy improves the *financial returns* to firm R&D investment remain unaddressed by empirical research.

To fill this gap, I examine how and when strong trade secret protection improves firm's financial returns to R&D investment (hereafter firm R&D productivity). Drawing on the literature on knowledge disclosure (Arrow 1962; Bhattacharya and Ritter 1983; De Fraja 1993; James and Shaver 2008; Polidoro 2006), I propose that the effectiveness of secrecy depends on a tension between two distinct mechanisms of knowledge disclosure – ex ante uncertainty reduction and ex post knowledge diffusion (Arrow 1962). That is, the successful commercialization of inventive knowledge often requires some ex ante reduction in uncertainty about the quality of the knowledge but, once inventive knowledge is disclosed, anyone who understands the knowledge may no longer be willing to pay for it (Arrow 1962). Indeed, trade secrecy that requires non-disclosure of knowledge can improve R&D productivity by preventing the spillover of proprietary knowledge to competitors. However, trade secrecy may make it difficult to use the knowledge disclosure as a means to reduce uncertainty of its knowledge. Consequently, it may hinder the firm's abilities to sell proprietary knowledge and to collaborate with external parties in commercialization process (Cassiman and Veugelers 2006).

In light of this tension, I argue that the effect of trade secrecy on firm R&D productivity depends on a firm's use of other knowledge appropriation mechanisms and on industry conditions. For example, a firm's reliance on patents may weaken the effect of trade secrecy on firm R&D productivity due to the disclosure requirements of patents. In contrast, a firm's investment in downstream activities strengthens the effect of trade secrecy because, without downstream complementary assets, the firm may have to disclose its proprietary knowledge to persuade external, downstream partners to be involved in the commercialization process. I also argue that the complexity of industry technology increases the effectiveness of trade secrecy. Finally, I argue that industry concentration increases the value of trade secrecy because firms in concentrated industries tend to be highly integrated and less dependent on external collaborators that could eventually become disruptive competitors.

To empirically examine the effect of strong trade secret protection, I exploit a natural experiment provided by the staggered implementation of the Uniform Trade Secrets Act (UTSA) across 46 states in the United States between 1975 and 2006. The enactment of UTSA provides an exogenous source of variation in the protection of trade secrets, which are usually unobservable (Png and Samila 2015). By employing a difference-in-differences approach, I find causal evidence that stronger trade secret legal protection leads to higher firm R&D productivity. I also find evidence that the concurrent use of other appropriation mechanisms and the existence of certain industry conditions moderate the effectiveness of trade secrecy. Specifically, an increase in the number of a firm's patents weakens effect of trade secret legal protection on firm R&D productivity. In contrast, an increase in a firm's investment into downstream complementary assets increases the effect of trade secret legal protection. Regarding industrial conditions, I find that the complexity of industry technology increases the effect of trade secret protection on the firm R&D productivity. I also find evidence that the effect of strong trade secret legal protection is more pronounced in highly concentrated industries. Taken as a whole, my findings provide a consistent pattern of evidence suggesting that the effectiveness of trade secrecy as an appropriation strategy depends on the value of disclosure or concealment of the inventive knowledge through other avenues.

In sum, this study makes contributions to the literatures on trade secrecy and knowledge appropriability. To date, studies of trade secrecy have focused on how strong trade secret legal protection affects firms' upstream activities, such as patenting, R&D investment, and other financial policies (Contigiani et al. 2018; Klasa et al. 2018; Png 2017a, b). However, to the best of my knowledge, no previous studies have examined the influence of trade secrecy on the *value* that firms capture from their R&D investments – a fundamental question in appropriability literature (Teece 1986). Prior research has raised questions about the efficiency of trade secret in the product commercialization process (Png 2017b), and this study addresses those questions by suggesting that trade secrecy does improve the financial outcomes of R&D investments. Moreover, this study offers insights to practitioners by demonstrating the contingent effect of trade secrecy on R&D productivity in the face of varying industrial conditions and the concurrent use of other knowledge appropriation mechanisms.

3.2. THEORETICAL BACKGROUND

Appropriability refers to the degree to which firms capture value from their inventions (Ceccagnoli and Rothaermel 2016; Teece 1986). While creating valuable and rare inventions is a necessary step for firms to benefit from R&D investment, doing so is insufficient to capture value from their inventions (Ceccagnoli and Rothaermel 2016; Teece 1986). Innovative firms may capture higher returns to their inventions when having successfully commercialized its inventions while preventing competitors from imitating the inventions. When protected from competitors, the firm's inventive knowledge may help gain larger profits from highly differentiated products or from lower cost production in commercialization process (Ceccagnoli 2005). Indeed, empirical studies have provided evidence attesting to benefits that the strong protection of inventive knowledge by appropriation mechanisms can bring to the firm such as the increase in firm market value and in innovation productivity (Ceccagnoli 2009; Hall, Jaffe and Trajtenberg 2005; Henderson and Cockburn 1994; McGahan and Silverman 2006).

Primary means by which firms capture returns to their inventions include patents, secrecy, lead time advantage, and complementary assets (Ceccagnoli and Rothaermel 2016;

Cohen et al. 2000). In contrast with other means, trade secrecy requires non-disclosure of the firm's inventive knowledge. According to UTSA, a trade secret is defined as any information (e.g., compilations, programs, formulas, techniques, processes, and methods) by which economic advantage can be obtained when maintained as secret and that can be kept secret by reasonable efforts. Given that such proprietary knowledge comprises of 70 - 80 percent of the value of U.S. company's intangible assets in knowledge-intensive industries (Schwarts and Weil 2010; U.S. Chamber of Commerce 2014), it is important for scholars and practitioners to understand the benefits and disadvantages that trade secrecy as an appropriation mechanism can bring to the firm. Indeed, a predominant stream of empirical research has utilized the exogenous increase in trade secret legal protection and examined how trade secret legal protection affects firm's upstream R&D strategies (Png 2017a, b) and firm's financial policies (Klasa et al. 2018). However, there has been surprisingly little empirical research examining how trade secrecy affects firm financial returns to R&D activities – the fundamental question in appropriability literature (Teece 1986). Indeed, in their comprehensive review of appropriability literature, James et al. (2013) urged researchers to examine how secrecy helps the firm capture value from its inventions. In response to this call, I propose a theoretical explanation to examine the relationship between trade secrecy and firm financial returns to R&D activities.

In what follows, I utilizes the observable institutional changes – the increase in trade secret legal protection – in order to overcome the unobservability of trade secrecy and I develop my theoretical argument about the relationship between strong trade secret legal protection and firm R&D productivity, that is, how the increase in trade secret protection affects firm R&D productivity.

3.2.1. The effect of trade secret legal protection on firm R&D productivity

I develop my theoretical argument about the effect of strong trade secret legal protection on firm R&D productivity by drawing on the tension between two distinct mechanisms of knowledge disclosure – ex ante uncertainty reduction and ex post knowledge diffusion (Arrow 1962). On the one hand, strong trade secret legal protection may reduce the disclosure of the firm's knowledge, thereby, minimizing the knowledge spillover to competitors. On the other hand, strong trade secret legal protection may make it difficult to use knowledge disclosure as a means to reduce uncertainty about the firm's inventive knowledge in commercialization process, all else being equal (Arrow 1962; Bhattacharya and Ritter 1983; De Fraja 1993; James and Shaver 2008; Polidoro 2006).

Strong trade secret legal protection may reduce knowledge spillovers to competitors, thereby, increasing the benefits from commercializing the firm's inventive knowledge. Strategy literature has tied the uniqueness of knowledge to its value (Barney 1991; Grant 1996). Thus, scholars have focused on how the firm maintains inventive knowledge unique by preventing competitors from imitating it (Dierickx and Cool 1989; Zander and Kogut 1995). When inventive knowledge remains unique, the firm can extract larger profits from the inventive knowledge than competitors who do not possess the same or similar knowledge. Therefore, strong trade secret legal protection that minimizes knowledge disclosure may bring benefits to the firm. Specifically, strong trade secret legal protection may conceal the firm's knowledge, thereby, making difficult competitors' assessment of the firm's knowledge – a necessary step to imitate the knowledge (Anton and Yao 2004; Arrow 1962). Such non-disclosure of knowledge may allow the firm to hide from competitors what knowledge the firm possesses and how valuable the knowledge is, which, in turn, deter knowledge spillover to competitors that occurs only when the competitors understand and use the firm's knowledge (Griliches 1991). Supporting this view, theoretical literature suggests that firms often prefer secrecy to formal intellectual property rights because the concealment of proprietary knowledge by trade secrecy may deter competitors' attempts to imitate or invent-around the firm's knowledge (Anton and Yao 2004; Horstmann, MacDonald and Slivinski 1985; Zaby 2010). Consequently, the firm's valuable proprietary knowledge may allow the firm to enjoy profits in commercialization process relative to competitors who do not know or use such valuable inventive knowledge (Barney 1991; Grant 1996). Therefore, based on the above argument I propose that strong trade secret protection can have a positive impact on the firm R&D productivity in two ways. First, in the commercialization process prevention of the disclosure of the firm's knowledge may reduce spillover early stage R&D to competitors. Knowledge of early stage R&D such as creative ideas and failure experiences is often an important source for quality inventions and derivative future ideas. For instance, although creative ideas are rudimentary in early stage R&D, it may become a seed for future inventions and derivative inventions spawned by the initial idea often have far greater commercial value (Ahuja, Lampert and Novelli 2013). Thus, the concealment of knowledge about early stage R&D may prevent competitors from building on the firm's inventions, thereby, allowing the firm to benefit from monetizing such derivative inventions. Moreover, knowledge concealment by trade secrecy may prevent competitors from vicariously learning from the firm's failure experiences (Baum and Dahlin 2007; Chuang and Baum 2003) in early stage R&D such as totally failed experiments and the inventions that do not meet customer needs. Prior research shows that failures in inventive efforts enables the firm to learn from them and create quality inventions (Khanna, Guler and Nerkar 2016). Thus, by preventing competitors from vicariously learning from the firms' failure experiences the firm can builds on its failures to create valuable inventions and improve its benefits in commercialization process. Second, the prevention of knowledge disclosure by trade secrecy may also lower the spillover of the firm's product and process innovations (i.e., inventions that have been commercialized as products or implemented as manufacturing processes). Recent empirical study shows that product market spillover leads to lower firm growth presumably due to the decrease in product margin or investors' lower expectation about the firm growth (Bloom, Schankerman and Van Reenen 2013). Likewise, although there might be a relatively lower chance that process inventions developed in house leak out to competitors, the tacit knowledge of process inventions embedded in organizational practices and routines (Nelson and Winter 1982) often spills over to competitors by the firm's employees or former employees (Ottoz and Cugno 2008). In such cases, the firm might be less likely to enjoy low cost advantage in commercialization process. Thus, preventing the disclosure of the firm's product and process knowledge may help benefit more from higher product margin or lower cost advantage in commercialization process.

However, strong trade secret legal protection may also make it difficult to use knowledge disclosure as a means to reduce uncertainty about the firm's inventive knowledge in commercialization process, all else being equal (Arrow 1962; Bhattacharya and Ritter 1983; De Fraja 1993; James and Shaver 2008; Polidoro 2006). Because trade secrecy can protect only "undisclosed" knowledge it may be extremely difficult for the firm to use knowledge disclosure as a means to signal the quality of its inventive knowledge when trade secret legal protection is strengthened. Thus, I argue that strong trade secret legal protection can have a negative impact on the firm R&D productivity. Specifically, strong trade secret legal protection may lead the firm to suffer from information asymmetry caused by concealment of the firm's inventive knowledge in commercialization process. The firm often needs to gain external resources in commercialization process that the firm lacks such as downstream manufacturing or distribution capacity (Teece 1986); the firm also often license out its technology in technology market or conduct collaborative R&D in commercialization process (Arora, Fosfuri and Gambardella 2001a). In such cases, knowledge disclosure may function as a means of reducing uncertainty about the value of firm's inventive knowledge to facilitate the commercialization process (Arrow 1962; Bhattacharya and Ritter 1983; De Fraja 1993; James and Shaver 2008; Polidoro 2006). However, strong trade secret legal protection that conceals knowledge inside the organization may cause information asymmetry between the firm and external environment. Thus, the firm may spend considerable transaction costs to reduce information asymmetry in commercialization process. Although the firm can design legal processes such as non-compete agreement (Dexter and Park 2003) and may still be able to use knowledge disclosure as a quality signal, these processes not only take away considerable resources that might have been used for improving the quality of innovation; further, they also slow down the commercialization process. Therefore, strong trade secret legal protection may decrease firm R&D productivity.

In spite of contradictory logics about the effect of trade secrecy on firm R&D productivity, extant literature offers no conclusive evidence. In this study, I argue that the benefits of non-disclosure by strong trade secret legal protection outweigh disadvantage due to the decrease in knowledge disclosure, all else being equal. Valuable knowledge may confer sustainable competitive advantage *only* when the knowledge remains inimitable (Barney 1991). Once knowledge spills over, competitors may enter into the firm's inventive domain (Jaffe 1986) and competitors may imitate the firm's knowledge with little costs (Arrow 1962). Consequently, the firm may gain lower profits from its inventions. Thus, appropriability literature suggests that preventing knowledge spillover may increase the fraction of value the firm captures from its own inventions (Ceccagnoli and Rothaermel 2016; James et al. 2013; Teece 1986). Among appropriation mechanisms, trade secrecy has been rated as the most efficient in preventing knowledge spillover to competitors by R&D managers (Cohen et al. 2000; National Science Foundations 2008). Thus, when utilizing trade secrecy as an appropriation mechanism firms may gain substantial benefits by commercializing unique knowledge that competitors do not know. In contrast, firms disclose its knowledge *only* when there are the benefits from doing so because of knowledge expropriation risks (Bhattacharya and Ritter 1983; Diamond 1985; Verrecchia 1983). For instance, firms may spill over its knowledge to other competitors unwillingly while disclosing its knowledge to external collaborators, thereby, decreasing the firm's profits from its inventions. Another downside of knowledge disclosure is that the firm becomes vulnerable to opportunism of competitors and external collaborators. Consequently, the firm may need to monitor the external parties that learned the firm's inventive knowledge. Further, knowledge disclosure may decrease the fraction of value the firm captures from its own inventions because the firm shares with external collaborators the value captured from its inventions in commercialization process. Due to such expropriation risks, monitoring costs, and share of value captured in commercialization process the benefits of knowledge disclosure in general may be smaller even when knowledge disclosure decreases information asymmetry between the firm and external collaborative parties. Therefore, I argue that knowledge disclosure in general engenders a higher level of risks and firms may spend considerable cognitive resources in executing and monitoring the process of knowledge disclosure to external parties.

In sum, I argue that knowledge concealment by trade secrecy may provide certain benefits to the firm; in contrast, knowledge disclosure engenders higher risks and requires considerable cognitive resources due to potential opportunistic behaviors of external parties. Thus, the benefits of knowledge concealment in general outweigh the disadvantages caused by the lack of knowledge disclosure. Following is my hypothesis:

Hypothesis 1 (H1): The increase in trade secret legal protection will increase firm R&D productivity.

I now turn to examine the contingent effects of other appropriation mechanisms employed by the firm. In my baseline hypothesis, I argue that strong trade secret legal protection may enable the firm to tightly conceal and protect its proprietary knowledge, thereby, improving firm R&D productivity. However, the strength of Hypothesis 1 should depend upon the degree to which other appropriation mechanisms also favor the knowledge concealment over the knowledge disclosure. That is, the effect of exogenous trade secret protection may be stronger for firms utilizing appropriation mechanisms that also promote knowledge concealment rather than knowledge disclosure. In this study, I focus on the concurrent use of patent and of downstream complementary assets and in what follows, I discuss how each appropriation mechanism – patents and complementary assets – moderates the effect of strong trade secret legal protection on firm R&D productivity.

3.2.2. The effect of patents on the relation between trade secret protection and firm R&D productivity

In contrast with trade secrecy, patent as an appropriation mechanism may make firms to utilize knowledge disclosure rather than knowledge concealment. Thus, I argue that the effect of strong legal protection of trade secrets may be weaker for firms possessing a larger number of patents.

First, application to a patent requires the disclosure of the firm's knowledge. Specifically, patent system provides the inventor with exclusive rights on the invention for limited duration (e.g., 20 years in the United States) in exchange for the disclosure of invention to the extent that the individuals skilled in the art must be able to understand the invention. If a firm has a larger number of patents, the patented knowledge has been already disclosed. The knowledge, once disclosed and became observable by competitors, cannot be concealed by trade secrecy. Thus, strong trade secret legal protection may be less likely to protect knowledge of the firm possessing a larger number of patents, all things being equal.

Second, firms often strategically use patents to seek other benefits (Somaya 2012). In such cases, a firm utilizes patents to *disclose* its knowledge in order to signal the quality and potential value of the firm's knowledge and, by doing so, the firm may seek benefits from external parties (Bhattacharya and Ritter 1983; De Fraja 1993; Gans, Hsu and Stern 2008; James and Shaver 2008; Polidoro 2006). Empirical studies support this argument; innovative firms that actively collaborates with external parties are more likely to patents in order to not only protect its knowledge but also signal to external collaborators (Arora, Athreye and Huang 2016). In technology market the granted patents are more likely to result in technology licensing agreement (Gans et al. 2008) and that firms with larger number of patents are more likely to cooperate in technology market by licensing in or licensing out technologies (Gans, Hsu and Stern 2002). Further, in strategic factor market, patents function as a quality signal and help a firm seek external financial resources (Hsu and Ziedonis 2013). These findings may suggest that firms with a larger number of patents might be more likely to utilize an appropriation strategy that discloses the firm's knowledge and seek external resources from third parties. When a firm discloses its knowledge, it should do so to the extent that the potential "buyer" can understand and assess it. Because understanding and assessing knowledge requires investigation of the knowledge at a granular level (Spender and Grant 1996; Winter 1987), the firm utilizing patents to seek external resources is less likely to conceal its knowledge.

Last, the mechanisms of deterring knowledge spillover by patents disclose the firm's knowledge rather than conceal them (Clarkson and Toh 2010). Although patent system confers an exclusive right on an invention to the inventor, survey evidence suggests that patents do not provide strong appropriability in R&D intensive industries; a major concern for firms using patents as appropriation mechanism is, ironically, the disclosure of its knowledge and the narrow scope of protection conferred by patents (Cohen et al. 2000; Levin, Klevorick, Nelson, Winter, Gilbert and Griliches 1987). As a result, it is often fairly easy for competitors to invent around or to build on a firm's patent without infringing it (Rivera and Kline 2000; Zaby 2010). Thus, in order to prevent competitors from inventing around or building on the firm's patents, the firm can use diverse mechanisms such as patent fences for "blocking" others (Ceccagnoli 2009; Cohen et al. 2000), proprietary fences around the focal firm's own patents (i.e., self-citations) (Ahuja et al. 2013; Hall et al. 2005), geographic dispersion of prior arts as isolating mechanism (Kim 2016), patent reexamination as keep-out sign (Clarkson and Toh 2010), and patent litigations (Graham and Somaya 2004; Polidoro and Toh 2011; Somaya 2003). The findings from these empirical studies show that these mechanisms may improve firm market value (Ceccagnoli 2009; Hall et al. 2005) and firm financial performance (Kim 2016); further, these mechanisms may preclude competitors from invading the firm's inventive domain (Clarkson and Toh 2010; Kim 2016). Firms, indeed, often utilize these mechanisms; for instance, while developing its Sensor shaver, Gillette chose only one of the seven blade designs initially developed for Sensor shaver after careful examination of patent landscapes because the chosen one was considered most difficult for its competitors to invent around (Rivera and Kline 2000). Moreover, Gillette filed 22 patents around the chosen design (i.e., patent fences) in order to completely block competitors from duplicating the product. These different mechanisms all require the disclosure of the firm's knowledge; most of the mechanisms (except for geographic dispersion of prior arts) also allows competitors to even understand the firm's knowledge. However, these mechanisms still prevent competitors from *using* the knowledge by *showing* its patent fences or stakes rather than by concealing the firm's knowledge.

Overall, these arguments suggest that firms possessing a larger number of patents may be more likely to disclose their knowledge to reduce the uncertainty about the value of knowledge to potential "buyers" and/or to develop deterring mechanisms that disclose knowledge. Thus, firms with a larger number of patents may be less likely to benefit from strong trade secret protection that only protects “undisclosed” knowledge. my arguments are in line with theoretical literature and recent empirical studies suggesting that patents and trade secrecy may be a substitute. Theoretical literature suggests that there is a stark trade-off between the benefits and costs of using patents and those of using trade secrecy due to the disclosure requirement of patents vis-à-vis the non-disclosure requirement of trade secrecy (Anton and Yao 1994, 2004; Friedman, Landes and Posner 1991). Recent empirical study also shows that stronger trade secret protection leads to the immediate decrease in firms’ patenting (Png 2017b). Thus, the benefits from stronger trade secret protection that requires the non-disclosure of knowledge may be smaller for firms possessing a larger number of patents. Following is my hypothesis:

Hypothesis 2: The increase in trade legal secret protection will increase firm R&D productivity to a lesser extent for firms possessing a larger number of patents.

3.2.3. The effect of complementary assets on the relation between trade secret protection and firm R&D productivity

Complementary assets are critical in commercializing inventions (Teece 1986). In particular, competitive manufacturing capacity and distribution channels may enable firms to enjoy economies of scale and consequent lower cost advantage. Further, the learning effect from large scale manufacturing may help improve the quality of products in commercialization process (Ceccagnoli and Rothaermel 2016). Another important role of complementary assets is that the degree to which the firm capture the fraction of value from its inventions may also depend on the possession of complementary assets and on the bargaining power the firm has over the downstream partners that own complementary assets (Teece 1986).

I argue that firms investing into more downstream complementary assets such as competitive manufacturing and distribution channels may be more likely to conceal its knowledge in commercialization process. Commercialization of an invention consists of upstream activities such as research and development as well as downstream activities such as competitive manufacturing and distribution of products (Teece 1986). Focusing on either downstream or upstream activities may require the firm to collaborate in the technology market with third parties possessing the resources that the firm lacks (Arora et al. 2001a; Gans and Stern 2010). For instance, if a firm possesses only upstream capabilities, the firm might be more likely to seek a third party with necessary downstream complementary assets in vertical technology market (Arora et al. 2001a; Arora, Fosfuri and Gambardella 2001b). In such cases, the firm needs to persuade the third party with the necessary assets to be involved in the firm's commercialization process. Due to the information asymmetry between two parties, the firm may have to disclose its knowledge to the extent that the third party fully understands and assesses the potential value of the firm's knowledge (Bhattacharya and Ritter 1983). In such cases, trade secrecy that requires non-disclosure of knowledge may be less likely to bring benefits to the firm and the negative effect of trade secrecy – the increase in information asymmetry – will be more pronounced. In contrast, if a firm actively invests into downstream complementary assets, the firm may be less likely to disclose its knowledge and to interact with third parties in commercialization process, all else being equal. Rather, the firm may be able to produce and distribute its products in house while keeping its knowledge concealed. Therefore, strong trade secret legal protection may help firms with more downstream complementary assets protect their knowledge and thus maintain and/or enhance their competitiveness over competitors in the commercialization process. That is, with a stronger trade secret protection a firm with downstream complementary assets may be able to capture a larger portion of its inventions from upstream to downstream activities of commercialization process relative to the firm without downstream complementary assets. Thus, I hypothesize:

Hypothesis 3: The increase in trade secret legal protection will increase firm R&D productivity to a greater extent for firms investing into more downstream complementary assets.

Appropriability literature suggests that the effect of appropriation strategies may depend on the environmental conditions such as appropriability regime (Cohen et al. 2000; Zhao 2006), industry R&D intensity (Hill 1992; Kafouros and Buckley 2008), industry technology complexity (Contigiani et al. 2018; Levin et al. 1987; Png 2017a) and industry life cycle (Boldrin and Levine 2013). Indeed, survey evidence suggests that the effectiveness of appropriation mechanisms are different across industries (Cohen et al. 2000; Levin et al. 1987). Given the impact of external environment on firm strategy to gain competitive advantage, the effect of environmental conditions on appropriation strategy is not surprising. Thus, extending extant literature, my study examines two condition of industrial environment – industrial technology complexity and industry concentration – and I argue that the contingent effects of industrial condition may depend on whether the industrial environment promotes the focal firm to conceal or disclose its knowledge in commercialization process. Examining these conditions may help us not only develop boundary conditions of my baseline hypothesis but test the consistency of my logics behind Hypothesis 1.

3.2.4. The effect of trade secret protection on firm R&D productivity in complex vs. discrete industries

I expect the effect of stronger trade secret legal protection on firm R&D productivity to be stronger for firms in complex technology industry relative to firms in discrete technology industries. Complex technology consists of a larger number of knowledge components while discrete technology is comprised of few knowledge components (Cohen et al. 2000). For instance, a computer product, classified as complex technology, may be comprised of a few hundreds of knowledge components while drug or metal product, classified as discrete technology, tends to be comprised of a small number of knowledge components. Although the commercialization process might be different between the two groups of industries due to the degree of product complexity, I argue that the difference in the efficiency of knowledge disclosure between two groups of industries and the consequent decrease in the value of knowledge disclosure in complex technology industry may make the effect of stronger trade secret legal protection more pronounced in complex technology industry than in discrete technology industry.

In a complex technology industry a firm's knowledge, when disclosed, may be inaccurately assessed by a third party relative to in a discrete technology industry (Levin et al. 1987). The reason of difficulty in assessing the value of knowledge in complex technology industry may be found in the character of complex technologies such as the interdependence of knowledge components of a technology (Rivkin 2000; Sorenson, Rivkin and Fleming 2006) or the multiple ownership of a complex technology (Cohen et al. 2000). In contrast, a firm in discrete technology may be able to clearly reveal the value of its knowledge to the potential "buyers". Indeed, Heeley, Matusik and Jain (2007), in their empirical study, show that knowledge disclosure of a firm in complex industry is more likely to lead investors to undervalue the firm's resources relative to discrete technology industry. Consequently, in industries characterized by complex technologies the concealment of knowledge might be a better appropriation strategy. Supporting this view, Graham and Hegde (2015) also show that secrecy is preferred in complex industries in their inventor-level analysis. Png (2017a) also shows that, when trade secret legal protection becomes stronger, firms in complex industries increase R&D activities. These empirical findings might suggest that firms in complex technology industries may preferably keep its knowledge undisclosed.

To summarize, the benefits of stronger trade secret legal protection in concealing the firm's knowledge may be stronger in complex industries. As discussed, knowledge disclosure to seek benefits from third parties may be less valuable in complex technology industries due to the difficulty in assessing the value of complex knowledge. As a result, firms in complex technology industries may be more likely to maintain its knowledge concealed relative to firms in discrete technology industries. In contrast, in discrete technology industries, firms likely use the disclose of its knowledge to seek external resources because valuation of disclosed knowledge is easier due to the simplistic nature of the technology. In discrete technology industry, the consequent preference of knowledge disclosure as a means of seeking external sources may amplify the negative effect of strong trade secret protection. Therefore, complex technology industry might provide an environment in which trade secrecy as an appropriation mechanism is more efficient relative to discrete technology industry. Thus, I hypothesize:

Hypothesis 4: The increase in trade secret legal protection will increase firm R&D productivity to a greater extent for firms in complex technology industries relative to firms in discrete technology industries.

3.2.5. The effect of trade secret protection on firm R&D productivity in highly concentrated industries

I propose that the effect of stronger trade secret legal protection on firm R&D productivity will be stronger for firms in highly concentrated industries relative to low concentrated industries. Highly concentrated industries are often characterized as a low competitive environment where few dominant players have established its commercialization process over time and have a large market share. Each of these firms is likely to have a strong pricing power and there may be a high entry barrier to the industry. In contrast, low concentrated industries are considered a highly competitive environment; in these industries the entrance of new firms may be easier but firms in these industries may have little pricing power and are more likely to fail (i.e., higher exit rate). Consequently, the firm in a low concentrated industry may be more likely to compete against competitors to gain more resources, to better position itself, and to survive.

I argue that in highly concentrated industries firms likely maintain its knowledge concealed in commercialization process. In highly concentrated industries a firm is less likely to need to seek external resources. Specifically, in low competitive environment (i.e., in highly concentrated industries), it is more likely that a firm has already established the commercialization process over time by, for instance, having developed organizational routines and practices of R&D, manufacturing, and distribution channels, and, if necessary, having formed ties with outsiders (Cantwell and Mudambi 2011). Consequently, firms in highly concentrated industries with higher rents and market share can easily take advantage of their deep pockets to deter new entrances; thus, they may be less willing to overturn the status quo and vertical integration in commercialization process may allow the firm to capture larger value from its inventions (Ceccagnoli and Rothaermel 2016). For firms in highly concentrated industries, therefore, the knowledge disclosure and attempts to collaborate with new external parties is less likely, all else being equal. Strong trade secret legal protection in such cases may help hide its inventive knowledge which confer the firms competitive advantage.

In contrast, in highly competitive industries(i.e., low concentrated industries), firms are more likely to seek external resources, learn from others, and look for partners in commercialization process (Williamson 1965) because the presence of a larger number of firms in an industry may be associated with higher ambiguity about strategic positions of firms and of products in the industry (Cohen and Klepper 1992; Sorenson 2000). Given the small amount of resources and little pricing power conferred to each firm in the industry, a firm may have to find external resources and partners that, when combined with the firm's knowledge, might optimize the outputs from commercialization process. Doing so may allow the firm to uniquely position itself and help survive in the competitive environment. Importantly, in process of finding valuable resources and partners, the focal firm may have to persuade the third party to participate in the firm's commercialization process. While searching for new resources and partners, the firm, therefore, may be more likely to disclose its knowledge to several firms as well as to attempt to carefully assess knowledge possessed by other firms in the industry. Disclosure of knowledge and careful assessment of others' knowledge may be, therefore, more prevalent in low concentrated industries relative to highly concentrated industries. When successfully combined with external knowledge, firms may create unique, innovative products or services which may increase their profits. In such cases, the strong trade secret protection that make it difficult to use knowledge disclose as a means to reduce information asymmetry may have a negative effect on firm R&D productivity.

To summarize, strong trade secret legal protection may be more likely to protect the knowledge of firms in highly concentrated industries relative to firms in low concentrated industries. In highly concentrated industries firms may be less likely to seek external resources to overturn the status quo. Thus, strong trade secret protection may conceal and protect the firms' knowledge in the commercialization process. In contrast, in low concentrated industries firms may actively seek as well as evaluate external resources and ties in order to survive and find a better position in the industry. The consequent disclosure of knowledge of firms in low concentrated industries may lead to weaker legal protection of trade secrets. Based on the discussion above, I hypothesize:

Hypothesis 5: The increase in trade secret legal protection will increase firm R&D productivity to a greater extent for firms in highly concentrated industries.

3.3. RESEARCH DESIGN

3.3.1. Uniform Trade Secret Acts (UTSA)

Since the recommendation for enactment of Uniform Trade Secrets Act (UTSA) by the National Conference of Commissioners in 1979, the Uniform Trade Secrets Act (UTSA) has been enacted in 46 states. Prior research has shown that macro-level environments such as economic or political conditions or lobby efforts of firms did not influence the enactment of USTA (Png and Samila 2015). Thus, prior studies have used UTSA as the source of variation in trade secret protection and examined the effect of trade secrecy (Png 2017a, b). It may be worth noting the ways UTSA strengthened the protection of trade secrets in three ways: first, the scope of trade secret legal protection expanded from the secrets that are only in continuous use or business-related to any proprietary knowledge including negative know-how (i.e., failure experiences). Second, the mere possession of others' trade secrets without actual use is also classified as misappropriation of trade secrets under UTSA. Further, owners of trade secrets are given a longer time – three years – to begin a litigation which may reduce the incentives for misappropriation. Last, up to twice of the actual damages is allowed as the punitive damages for misappropriation. Thus, UTSA enactment increased trade secret legal protection and my study examines how the increase in trade secret legal protection affect firm R&D productivity by using the staggered enactment of UTSA.

3.3.2. Sample and data

Our main data for empirics comes from three sources: (1) Compustat within Wharton Research Data Services (WRDS), (2) Research Quotient (RQ) within WRDS, and (3) U.S. patents database by Kogan, Papanikolaou, Seru and Stoffman (2017). Compustat contains financial information and other firm level information for U.S. public firms such as industry classification and state of headquarter locations. RQ database provides research quotient variable between 1975 and 2015 – firm-specific output elasticity of R&D (Cummings and Knott 2018; Knott 2008) – which is used as dependent variable in this study. I construct patent variable using U.S. Patents database by Kogan et al. (2017) and this database provides patent information between 1926 and 2010 with associated firm identifiers (i.e., PERMNO).

In order to construct my sample, I focus on U.S. public manufacturing firms (SIC 200 – 399) because appropriability has been a critical issue in manufacturing industries (Cohen et al. 2000). Due to data restriction of patent data and RQ database, my sample consists of manufacturing firms between 1975 and 2010. Last, following prior study (Cummings and Knott 2018), I restrict my sample to firm-year observations with research expenditure of at least USD 1 million due to volatility of research quotient for firms with R&D expenditure under this threshold. With these criteria, I am left with a final sample of 27,494 firm-year observations from 1975 to 2010.

3.3.3. Empirical model and variables

I run ordinary least squares (OLS) regressions to examine hypotheses in this study. Specifically, I estimated the following regression:

$$\mathrm{RQ}_{ist+1} = \alpha_i + \alpha_t + \beta_1 UTSA_{st} + \gamma \boldsymbol{X}_{ist} + \varepsilon_{ist}$$

Where i indexes firm, s indexes state and t indexes year. α_i is firm fixed effects which control for time-invariant heterogeneity among companies and α_t is year fixed effects which control for year effect. Following prior study (Castellaneta, Conti and Kacperczyk 2017), I construct UTSA $_{st}$ as a dummy variable; it is coded "1" for any year t in which the Uniform Trade Secret Act (UTSA) has been enacted in state s ("treatment" group) and it is coded "0" otherwise ("control" group). In my main analyses, I use corporation's state of headquarter information because large firms' R&D units tend to be not geographically dispersed but to be located close to the firm's headquarters (Acharya, Baghai and Subramanian 2013; Breschi 2008; Howells 1990). RQ $_{ist+1}$ represents research quotient as a proxy for firm R&D productivity and $\boldsymbol{X}_{ist}$ represents time-varying characters of firm i. ε_{ist} is the error term and in order to account for serial correlation of the error term, I cluster standard errors at the state of headquarter level (Bertrand, Duflo and Mullainathan 2004). There is a one-year lag between dependent variable – RQ – and other variables for causality of my analysis. The UTSA is the primary variable of interest (i.e., the independent variable of my study). Thus, the coefficient of interest is β1, which measures the effect of the stronger trade secret protection on firm R&D productivity and my baseline hypothesis – Hypothesis 1 – predicts that the coefficient β1 will be positive and significant.

RQ (Research quotient) – my dependent variable – represents the percentage increase in revenue from a 1% increase in R&D while keeping others constant (Cummings and Knott 2018; Knott 2008). Thus, RQ is similar to the means most commonly used by economists to measure industry-level returns to R&D activities (Hall 1993; Hall, Mairesse and Mohnen 2010) but it is constructed as the firm-level. RQ has advantages over other proxies for innovation productivity such as patent intensity and total factor productivity (TFP); patent intensity – often operationalized patents weighted by R&D – does not account for innovations without being patented (i.e., kept secret) and only explains firms' upstream R&D activities while RQ is estimated by comparing a firm's dollar input with its dollar output. Further, in contrast with TFP that captures contributions of all omitted variables as R&D productivity while RQ captures only the contribution of a firm's own R&D activities. RQ is exponent γ in firm's final goods production function:

$$Y = AK^{\alpha}L^{\beta}R^{\gamma}S^{\delta}D^{\phi}e$$

where Y is output, K is capital, L is labor, R is R&D, S is spillover, and D is advertising. Thus, RQ can be interpreted as a firm's capability to generate revenues from its R&D investment. Specifically, RQ variables, which are available from WRDS, are estimated using the following random coefficients model (Longford 1995) that allows firm-specific R&D elasticity output:

$$Ln\ Revenue = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i})\ Ln\ Capital \times (\beta_2 + \beta_{2i})\ Ln\ Employee +$$
$$(\beta_3 + \beta_{3i})\ Ln\ R\&D + (\beta_4 + \beta_{4i})\ Ln\ Spillover\ to\ focal\ firm + (\beta_5 + \beta_{5i})\ Ln\ Advertising$$

The β_3 represents direct effect of R&D on revenue and β_{3i} represents firm specific error. Thus, the sum of β_3 and β_{3i} (i.e., $\beta_3 + \beta_{3i}$) is RQ which represents firm specific R&D elasticity. Prior study shows that β_{3i} is significantly different from β_3, indicating that the capability to transform R&D investment into revenue is, indeed, heterogeneous across firms (Knott 2008). RQ variable is constructed using 10-year rolling window of Compustat data. Thus, for instance, the RQ for 2002 is estimated using data from 1993 and 2002. It is worth noting that "Spillover to focal firm" in the specification represents the sum of the difference between focal firm knowledge (R&D) and each competitor that has a larger knowledge stock than focal firm. Thus, "Spillover to focal firm" basically captures a focal firm's likelihood of encountering a superior knowledge and utilize the superior knowledge to increase revenue. Thus, RQ variable separates the effect of the firm's own R&D from the effect of industry spillover and the use of RQ as dependent variable reduces my concern that the focal firm's R&D productivity is driven by its ability to imitate competitors' knowledge rather than appropriating value from its own inventions.

Because RQ is estimated using the past 10-year rolling window of data, the effect of strong trade secret legal protection may be gradually incorporated in the firm RQ over the next 10 years after UTSA enactment. For instance, in the state of Pennsylvania, UTSA was enacted in 2004. The RQ variable in 2007 will reflect 4 years after UTSA enactment period for firms in Pennsylvania (i.e., 2004 – 2007) and will also reflect 6 years before UTSA enactment (i.e., 1998 – 2003) for firms in Pennsylvania. Given this gradual incorporation of RQ variable, I conduct robust check by using 10-year average control variables and the results are reported in Robustness check section.

Control variables

In my analyses, I control for firm-level and industry-level characteristics that may affect firm R&D productivity. I also control for the enactment of trade secret related law – Inevitable Disclosure Doctrine – and time-invariant firm characters and year effects.

Regarding firm-level characteristics, I control for ROA, downstream complementary assets, firm size, market to book ratio, R&D and patents. I control for ROA – operationalized earnings before interest and tax over total assets – which may affect a focal firm's search scope and search intensity in R&D activities, thereby, affecting firm R&D productivity (Greve 2003). I control for downstream complementary assets – operationalized as capital expenditure weighted by total assets – because complementary assets may facilitate commercialization process and, in turn, improve firm R&D productivity (Teece 1986). The use of capital expenditure may help accurately capture recent investment into downstream complementary assets such as competitive manufacturing and distribution channels. Firm size is operationalized as natural logarithm of employee and this variable is to control for the effect of firm's scale. I also control for market-to-book ratio which represents investment opportunities, thereby, affecting innovation policies and outcomes (Acharya et al. 2013; Png 2017a) and this variable is operationalized as natural logarithm of the ratio of market value (obtained as market value of common stock plus current and long-term debt plus preferred stock minus deferred taxes and investment tax credit) to the book value of total assets. I also control for R&D and patents; R&D are operationalized as natural logarithm of R&D expenditure and patents are operationalized as natural logarithm of the number of patent applications in the firm-year. R&D is an input to a focal firm's inventive efforts and patents are intermediate outputs of inventive efforts as well as an appropriation mechanism to capture value from inventions.

Regarding industry-level characteristics, I control for industry concentration, industry growth and industry turbulence. Industry concentration – operationalized as the ratio of the sum of largest four firms' sales to the sum of all firms in the industry (3-digit SIC) – may represent competition in the industry and the degree of competition may affect a firm's appropriation strategy. Also, prior studies show that industry concentration affect how firms conduct R&D – that is, creation of incremental inventions vs. novel inventions which may affect firm R&D productivity (Barbosa, Faria and Eiriz 2013; Dolfsma and van der Panne 2008). Industry growth and industry turbulence (Dess and Beard 1984) may affect commercialization outputs of firms in the industry. Following prior studies (Dess and Beard 1984), these variables are operationalized as follows:

$$y = b_0 \ + \ b_1 t + a_t$$

I regress industry sales (3-digit SIC) on time (the past ten years). Industry growth is the time coefficient estimate (β_1) and industry turbulence is the standard error of the time coefficient estimate (β_1). Both variables are scaled by the mean of the industry sales. Finally, I control for the enactment of Inevitable Disclosure Doctrine which has been enacted and/or rejected in 21 states between 1960 and 2006 and which strongly protects trade secret misappropriation from focal firm's former employees, thereby, may affecting firm R&D productivity driven by R&D

inputs. I also control for time-invariant firm characters and seasonal effects which are operationalized as firm fixed effect and year fixed effects, respectively.

3.4. RESULTS

Table 3.1 summarizes the descriptive statistics and pairwise correlations of variables used in this study. Table 3.2 presents the main results of the OLS regressions. As shown in Model 1, the impact of stronger trade secret legal protection by UTSA on firm R&D productivity is positive and significant at 5% level (β = 0.011, *p*-value = 0.023), supporting Hypothesis 1 – the non-disclosure of knowledge reduces knowledge spillover of focal firm, thereby, increasing firm benefits from commercializing its own inventions. In order to assess the contingent effects of another appropriation mechanism in concurrent use, I create interaction of UTSA and each of appropriation mechanisms – patents and downstream complementary assets (Meyer 1995). I use continuous variable for each moderating variable following prior studies (e.g., Marx, Strumsky and Fleming 2009; Png 2017a; Wang, Zhao and He 2015; Younge, Tong and Fleming 2015). According to Hypothesis 2, the impact of trade secret legal protection on firm R&D productivity should be weaker for firms with a larger number of patents due to the trade-off between the benefits and costs of using trade secrecy and those of using patents caused by non-disclosure requirement of trade secrecy and disclosure requirement of patents. Results in Model 2 and Model 6 provide support for Hypothesis 2: the interaction between UTSA enactment and patents is negative and significant (β = -0.006, *p*-value = 0.005 in Model 6). In contrast, trade secret legal protection should lead to higher firm R&D productivity for firms with higher downstream complementary assets because the focal firm's downstream assets help conceal its knowledge in commercialization process, as proposed in Hypothesis 3, and the results in Model 3 and 6 support this hypothesis (β = 0.193, *p*-value = 0.002 in Model 6). Last, I assess the contingent effects of industrial condition – industrial technology complexity and industry concentration. According to Hypothesis 4 and Hypothesis 5, trade secret legal protection should lead to higher firm R&D productivity for firms in complex technology industries and in highly concentrated industries because in these industries firms may benefit more by concealing its knowledge in commercialization process. Results in Model 4 and 6 provide support for Hypothesis 4: the interaction between UTSA enactment and complex technology industry (dummy) is positive and significant (β = 0.032, *p*-value = 0.000 in Model 6). my results also support Hypothesis 5: the interaction between UTSA enactment and industry concentration is positive and significant (β = 0.042, p-value = 0.006 in Model 6).

In sum, these findings show that stronger trade secret legal protection leads to higher firm R&D productivity. When a focal firm has a larger number of patents, the positive effect is less pronounced while, when a focal firm invests into more downstream complementary assets, the positive effect is more pronounced. In complex technology industries or highly concentrated industries, the effect of stronger trade secret legal protection on firm R&D productivity is stronger.

3.4.1. Robustness checks

To further corroborate my results, I conduct several robustness checks by extending my baseline analyses.

Alternative measures of UTSA

I re-estimate the baseline models with alternative operationalization of my UTSA measures. First, I construct firm-specific continuous UTSA variable by using information about inventors' geographic locations. Large firms' R&D units tend to be located close to the firm's headquarters (Acharya et al. 2013; Breschi 2008; Howells 1990) and, therefore, prior study examining the effect of law change on firm innovation uses corporation headquarter information as a proxy for corporation R&D location (Acharya et al. 2013). However, in order to check the sensitivity of my results, I use the geographic location of inventors reported in patents granted to the focal firm in last 10 years (i.e., t – 0 to t – 9) and the results from using this information are qualitatively similar to main regression results although the direct effect of stronger trade secret legal protection on firm R&D productivity becomes weaker than main analyses, as reported in Model 1 and 2 of Table 3.4. I use the location information in granted patents rather than patent applications in consideration of lag between application year and granted year and potential move of inventors during the lag period.

Second, I construct UTSA variable using the index developed by Png (2017a). The index was constructed by considering the intensity of change in each state. That is, depending on the strength of trade secret protection in a state prior to UTSA enactment the change in trade secret legal protection by UTSA may be different. Thus, in order to capture the heterogenous change in trade secret legal protection across states, I constructed the UTSA variable using the index developed by Png (2017a) and the regression results were qualitatively same (See Model 3 and 4 of Table 3.4).

10-year average of control variables

Our dependent variable is 10-year rolling measure of the percentage increase in firm revenue from a 1% increase in firm R&D. Thus, I constructed control variables by using 10-year average value of each control variable and conducted regression analyses. The results were qualitatively similar (See Model 5 and 6 of Table 3.4).

Endogeneity of interaction effects

Firms might change its patenting or investment into downstream complementary assets due to UTSA enactment and, if so, the interaction effect between UTSA and each of these variables might be driven by firms' behavioral change. To alleviate such potential endogeneity concern, I hold these variables constant from the year of UTSA enactment by using the pre-UTSA average value of each variable. The regression results with these variables remained the same (including baseline analysis as well as interaction effect analysis), as shown in Table 3.5.

Pre-existing trends and gradual incorporation of UTSA effect

In order to examine whether there was a pre-existing trend, I constructed variables from 3 years before UTSA to years after UTSA, shown in Table 3.3. My concern is that firm R&D productivity was increasing prior to UTSA enactment and the analyses merely capture the trend rather than the effect of UTSA enactment (i.e., reverse causality). The results in Table 3.3 show that there was no pre-trend and UTSA dummy became significant after UTSA enactment. In addition, the significant effect remains several years after UTSA (5, 6, and 7 years) as shown in Table 3.3. There is a still potential concern that my 10-year rolling variables observed after UTSA enactment somehow captures pre-existing trend. If there were pre-existing trend (i.e., if firm R&D productivity had increased prior to the UTSA enactment), there must be pre-existing trend close to the year of UTSA enactment. Thus, I constructed UTSA dummy variables from 8 years before UTSA enactment and there was no trend until the year of UTSA enactment showing that the effect was not driven by pre-existing trend.

3.5. DISCUSSION AND CONCLUSION

Employing a difference-in-differences analysis of a quasi-natural experiment provided by the staggered implementation of state-level trade secret protection law – Uniform Trade Secrets Act (UTSA), this study shows that strong trade secret legal protection increases firm R&D productivity. I also find stronger support for interactions of two appropriation mechanisms – patents and downstream complementary assets – and two industrial conditions – complex technology industry and industry concentration. Specifically, the effect of strong trade secret protection on firm R&D productivity is weaker for firms possessing a larger number of patents due to stark trade-off between non-disclosure requirement of trade secrecy and disclosure requirement of patents; in contrast, the effect is stronger for firms investing into more downstream complementary assets because the possession of downstream complementary assets may reduce the firm's knowledge disclosure as a means to seek external benefits from third parties in commercialization process. I also find that the positive effect of strong trade secret protection on firm R&D productivity is stronger for firms in complex technology industry because disclosure of knowledge is less preferable in complex technology industry due to the difficulty of assessment of complex technology. Last, I find that the positive effect of strong trade secret protection is stronger for firms in highly concentrated industries where firms may have already established commercialization process and extract higher rents and, consequently, they may be less likely to overturn the status quo by disclosing its knowledge and seeking external resources. Taken together, this study suggests that the fit between trade secrecy and another appropriation mechanism in concurrent use or industrial conditions may depend on whether another appropriation mechanism in concurrent use or industrial environment allows the firm to keep undisclosed the firm's proprietary knowledge being protected by trade secrecy.

Our study may provide implications to the literature examining the effect of innovation on firm performance. This literature has extensively examined how patents as a proxy for firm innovations affect firm performance (e.g., Cockburn and Griliches 1988; Hall et al. 2005; Kogan et al. 2017). In contrast, my study shows that trade secrecy has a positive effect on the returns to firm R&D activities. Given that the use of trade secrecy is more prevalent than patents (Cohen et al. 2000; Hall et al. 2014), the contribution of this study to the literature is non-trivial. In particular, this study implicates that firms may substitute between patents and trade secrecy and this choice may depend on the focal firms' benefits from disclosure of its knowledge vs. concealment of its knowledge in commercialization process.

Our study also makes contribution to appropriability literature. First, my study shows that trade secrecy has a positive effect on firm financial returns to R&D activities and the effect of trade secrecy is contingent upon concurrent use of other appropriation and industrial conditions. Second, I suggest that firms need to devise appropriation strategies in consideration of knowledge disclosure and collaboration with external partners. Indeed, recent research on appropriability has paid attention to how the firm can signal to others and reduce uncertainty about inventive knowledge in commercialization process (Arora et al. 2016; Laursen and Salter 2014; Miozzo, Desyllas, Lee and Miles 2016). The findings from this stream of research are inconclusive: they show that firm's using the moderate level of appropriation mechanisms is associated with higher level of external collaborations (Laursen and Salter 2014). However, each appropriation mechanism might have a different effect on such "open" innovations (Miozzo et al. 2016). Although my study indirectly implies that disclosing knowledge to persuade external collaborators affect the financial returns to R&D activities, my findings suggest that each appropriation mechanism, indeed, has a different fit with collaboration with external partners. Further, my study suggests that it is more efficient to use other appropriation mechanisms than trade secrecy when disclosure of knowledge is preferred in commercialization process.

Last, although my findings show that the impact of strong trade secret legal protection on firm R&D productivity is weaker for firms possessing a larger number of patents, trade secrecy and patents in some cases might be complements. For instance, firms may use trade secrecy for early stage R&D and use patents once the invention has been commercialized because early stage R&D cannot be protected by formal intellectual property rights. Another example is concurrent use of trade secrecy and patents by disclosing some portion of a firm's knowledge while concealing other portion of the knowledge – the partial disclosure of the firm's knowledge. For instance, Wyeth, a pharmaceutical company acquired by Pfizer in 2009, enjoyed its exclusive know-how of developing Premarin, the hormone replacement therapy drug, for a long time by utilizing both patents and secrecy; competitors were neither able to imitate the drug nor were they able to develop its generic drugs after expiration of Wyeth's patents because its extraction process has been maintained as a secret (Lobel 2013). It is also worth noting that the dependent variable of my study is the percentage increase in revenue from a 1% increase in R&D (Cummings and Knott 2018; Knott 2008). Thus, it might be the case that the combined use of patents and trade secrecy might increase absolute revenues of the firm while the increase in revenue relative to the increase in R&D might be lower, that is, the combined use might be just less efficient. Therefore, future study may examine under what conditions trade secrecy and patents can be simultaneously utilized and can be more efficient as an appropriation strategy.

I conclude by suggesting implications for managers and practitioners. My findings indicate that firms may be able to benefit from combining different appropriation mechanisms in commercialization process. However, the effectiveness of such appropriation strategy may depend on the fit between the appropriation mechanisms the firm uses in the commercialization process as well as on the industrial environment under which the firm executes its appropriation strategy. Therefore, managers and practitioners may have to be careful in examining its needs for knowledge disclosure in commercialization process and in choosing the right mix of appropriation mechanisms to gain optimal benefits from execution of appropriation strategies. However, before doing so, managers should first have to think about its industrial environment over which the firm has no control but which may eventually determine the effectiveness of its appropriation strategy.

Table 3.1. Pairwise correlations and descriptive statistics

N = 27,494; All correlations with an absolute value equal to or greater than 0.02 are statistically significant at $p < 0.05$.

	Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.	Firm R&D productivity	1.00												
2.	UTSA (dummy)	-0.07	1.00											
3.	ROA	0.20	-0.10	1.00										
4.	Firm size (log)	0.14	-0.16	0.37	1.00									
5.	Downstream complementary assets	0.03	-0.13	0.14	0.19	1.00								
6.	Market-to-book ratio (log)	-0.10	0.13	-0.35	-0.29	-0.01	1.00							
7.	R&D (log)	0.08	0.08	0.13	0.66	0.04	0.05	1.00						
8.	Patents (log)	0.10	-0.08	0.19	0.62	0.20	-0.03	0.62	1.00					
9.	IDD	-0.04	-0.18	-0.04	-0.01	-0.09	0.06	0.04	-0.05	1.00				
10.	Industry concentration	0.10	-0.09	0.27	0.25	0.07	-0.31	-0.11	0.02	-0.04	1.00			
11.	Industry growth	0.04	-0.11	0.01	0.00	0.12	0.04	0.00	0.09	-0.07	-0.17	1.00		
12.	Industry turbulence	-0.01	0.06	0.06	0.00	-0.02	-0.11	-0.04	-0.04	0.01	0.20	-0.47	1.00	
13.	Complex technology industry (dummy)	0.01	0.08	0.11	-0.13	-0.03	-0.12	-0.11	-0.04	-0.09	0.10	0.04	0.07	1.00
	Mean	0.13	0.53	0.01	1.36	0.05	0.90	2.72	1.37	0.42	0.60	0.05	0.02	0.66
	Standard deviation	0.13	0.50	0.26	1.27	0.05	0.48	1.57	1.54	0.49	0.19	0.06	0.02	0.48

Table 3.2. OLS regression results – The impact of strong trade secret protection on firm R&D productivity

Robust standard errors, clustered at state-level, reported in brackets.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Firm R&D productivity					
UTSA	0.011	0.021	0.001	-0.009	-0.012	-0.039
	[0.005]	[0.006]	[0.007]	[0.006]	[0.010]	[0.013]
UTSA × Patents		-0.006				-0.006
		[0.002]				[0.002]
UTSA × Downstream complementary assets			0.164			0.193
			[0.058]			[0.059]
UTSA × Complex technology industry				0.031		0.032
				[0.008]		[0.008]
UTSA × Industry concentration					0.034	0.042
					[0.016]	[0.015]
Downstream complementary assets	-0.159	-0.162	-0.243	-0.158	-0.160	-0.260
	[0.037]	[0.038]	[0.056]	[0.037]	[0.037]	[0.058]
ROA	0.032	0.032	0.032	0.033	0.032	0.034
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]
Frim size	-0.031	-0.031	-0.031	-0.031	-0.030	-0.031
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Market-to-book ratio	0.006	0.006	0.006	0.006	0.006	0.006
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
R&D	0.033	0.034	0.033	0.033	0.033	0.033
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Patent	-0.000	0.003	-0.000	-0.000	-0.000	0.003
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]
IDD	0.003	0.003	0.003	0.004	0.003	0.004
	[0.005]	[0.006]	[0.005]	[0.006]	[0.005]	[0.006]
Industry concentration	0.002	0.002	0.004	0.008	-0.017	-0.014
	[0.020]	[0.020]	[0.020]	[0.020]	[0.026]	[0.024]
Industry growth	0.012	0.012	0.012	0.009	0.012	0.010
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
Industry turbulence	-0.036	-0.041	-0.035	-0.032	-0.040	-0.038
	[0.051]	[0.052]	[0.051]	[0.051]	[0.051]	[0.051]
Constant	0.193	0.184	0.199	0.188	0.205	0.203
	[0.021]	[0.019]	[0.021]	[0.020]	[0.023]	[0.021]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,494	27,494	27,494	27,494	27,494	27,494
Adjusted R-squared	0.527	0.528	0.528	0.528	0.527	0.530

Table 3.3. OLS regression result - The impact of trade secret legal protection on firm R&D productivity

Robust standard errors, clustered at state-level, reported in brackets.

Variables	Model 1 Firm R&D productivity
UTSA (-3)	-0.000
	[0.004]
UTSA (-2)	-0.001
	[0.005]
UTSA (-1)	-0.002
	[0.007]
UTSA (0)	0.005
	[0.006]
UTSA (1)	0.012
	[0.006]
UTSA (2)	0.012
	[0.006]
UTSA (3)	0.013
	[0.008]
UTSA (4)	0.007
	[0.007]
UTSA (5)	0.016
	[0.007]
UTSA (6)	0.011
	[0.006]
UTSA (7)	0.012
	[0.008]
UTSA (8+)	0.008
	[0.009]
Constant	0.193
	[0.021]
Control variables	Yes
Firm fixed effects	Yes
Year fixed effects	Yes
Observations	27,494
Adjusted R-squared	0.527

Table 3.4. OLS regression results: Alternative trade secret protection measures

Robust standard errors, clustered at firm-level in Model 1 and 2 and at state-level in Model 3 - 6, reported in brackets. UTSA for Model 1 and Model 2 are calculated by the sum of firm-specific UTSA dummies, each weighted by the proportion of focal firm's R&D locations reported in the last 10-year granted patents; I use granted year because the location is accurately captured by granted year. UTSA in Model 3 and 4 are calculated by UTSA Index provided by Png (2017b); the average of such measure for missing states and years following prior study (Castellaneta et al., 2017). To be consistent with the operationalization of dependent variable, financial control variables in Model 5 and 6 are calculated as 10-year average value of each variable between t – 0 and t – 9 and R&D control variables between t – 1 and t – 10 and values with at least 6 observations within the 10-year window are used.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables			Firm R&D productivity			
UTSA	0.010	-0.044	0.025	-0.088	0.008	-0.049
	[0.007]	[0.025]	[0.011]	[0.025]	[0.005]	[0.017]
UTSA × Patents		-0.010		-0.011		-0.007
		[0.003]		[0.004]		[0.003]
UTSA × Downstream		0.153		0.439		0.156
complementary assets		[0.074]		[0.162]		[0.074]
UTSA × Complex		0.033		0.075		0.033
technology industry		[0.011]		[0.016]		[0.009]
UTSA × Industry		0.056		0.093		0.059
concentration		[0.030]		[0.030]		[0.017]
Downstream	-0.142	-0.221	-0.159	-0.280	-0.044	-0.141
complementary assets	[0.036]	[0.057]	[0.037]	[0.072]	[0.066]	[0.083]
ROA	0.056	0.059	0.032	0.033	0.009	0.010
	[0.015]	[0.015]	[0.011]	[0.011]	[0.004]	[0.004]
Frim size	-0.031	-0.033	-0.031	-0.031	-0.000	-0.002
	[0.005]	[0.005]	[0.007]	[0.007]	[0.005]	[0.006]
Market-to-book ratio	0.007	0.007	0.006	0.006	0.019	0.020
	[0.005]	[0.005]	[0.005]	[0.005]	[0.011]	[0.011]
R&D	0.034	0.036	0.033	0.033	0.009	0.010
	[0.004]	[0.004]	[0.003]	[0.003]	[0.004]	[0.004]
Patents	-0.001	0.005	-0.000	0.003	0.000	0.004
	[0.001]	[0.002]	[0.001]	[0.002]	[0.003]	[0.003]
IDD	0.009	0.010	0.002	0.003	0.003	0.005
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.006]
Industry concentration	0.007	-0.012	0.002	-0.021	-0.026	-0.047
	[0.022]	[0.027]	[0.020]	[0.025]	[0.026]	[0.026]
Industry growth	0.024	0.022	0.012	0.010	0.065	0.060
	[0.021]	[0.021]	[0.019]	[0.019]	[0.032]	[0.034]
Industry turbulence	0.012	0.010	-0.033	-0.037	-0.091	-0.110
	[0.060]	[0.059]	[0.051]	[0.051]	[0.179]	[0.179]
Constant	0.184	0.188	0.191	0.207	0.175	0.187
	[0.019]	[0.022]	[0.021]	[0.021]	[0.036]	[0.034]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,844	20,844	27,494	27,494	26,571	26,571
Adjusted R-squared	0.583	0.586	0.527	0.529	0.522	0.524

Table 3.5. OLS regression results: Alternative patents and downstream complementary assets measures

Robust standard errors, clustered at state-level, in brackets. Patents and downstream complementary assets variables are held constant from the year of UTSA enactment by using the pre-UTSA average value of each variable to alleviate any endogeneity concern. Doing so also limits the treatment-group sample to firms with at least one observation both before and after UTSA enactment.

	Model 1	Model 2
Variables	Firm R&D productivity	
UTSA	0.012	-0.049
	[0.005]	[0.012]
UTSA × Patents		-0.006
		[0.003]
UTSA × Downstream complementary assets		0.173
		[0.061]
UTSA × Complex technology industry		0.034
		[0.008]
UTSA × Industry concentration		0.058
		[0.015]
Downstream complementary assets	-0.264	-0.264
	[0.067]	[0.067]
ROA	0.041	0.044
	[0.022]	[0.022]
Frim size	-0.028	-0.030
	[0.004]	[0.005]
Market-to-book ratio	0.005	0.005
	[0.008]	[0.008]
R&D	0.033	0.033
	[0.003]	[0.003]
Patents	0.003	0.003
	[0.002]	[0.002]
IDD	0.004	0.005
	[0.005]	[0.005]
Industry concentration	0.016	-0.001
	[0.020]	[0.023]
Industry growth	0.018	0.015
	[0.022]	[0.022]
Industry turbulence	-0.029	-0.031
	[0.060]	[0.059]
Constant	0.185	0.193
	[0.016]	[0.017]
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	18,495	18,495
Adjusted R-squared	0.503	0.506

Table 3.6. Year of UTSA enactment (Until 2010)

State	Year of UTSA enactment
Alabama	1987
Alaska	1988
Arizona	1990
Arkansas	1981
California	1985
Colorado	1986
Connecticut	1983
Delaware	1982
Florida	1988
Georgia	1990
Hawaii	1989
Idaho	1981
Illinois	1988
Indiana	1982
Iowa	1990
Kansas	1981
Kentucky	1990
Louisiana	1981
Maine	1987
Maryland	1989
Michigan	1998
Minnesota	1981
Mississippi	1990
Missouri	1995
Montana	1985
Nebraska	1988
Nevada	1987
New Hampshire	1990
New Mexico	1989
North Carolina	1981
North Dakota	1983
Ohio	1994
Oklahoma	1986
Oregon	1988
Pennsylvania	2004
Rhode Island	1986
South Carolina	1992
South Dakota	1988
Tennessee	2000
Utah	1989
Vermont	1996
Virginia	1986
Washington	1982
West Virginia	1986
Wisconsin	1986
Wyoming	2006

4. STANDING GROUND? THE INFLUENCES OF KNOWLEDGE DISPERSION AND TECHNOLOGY OPPORTUNITY ON GENERATIVE APPROPRIATION

4.1. INTRODUCTION

In addition to its commercial value, an invention can function as “a seed for future concepts and ideas” (Ahuja et al., 2013, p. 248). Thus, when firms search for new inventions, the starting point of the search is often their existing inventions (Nelson and Winter, 1982). Indeed, prior inventions often reduce the cost and uncertainty of developing subsequent, related inventions (Foster, 1988, March, 1991). Further, repeated use of prior knowledge can improve firms’ innovation capabilities (Katila and Ahuja, 2002) and the rearrangement of existing knowledge components can produce valuable new inventions (Henderson and Clark, 1990). However, given these advantages, competitors often can also benefit from building on a focal firm’s inventions (Katila, 2002, Rosenkopf and Nerkar, 2001) and such competitive appropriation of ideas could cost focal firms future revenues. For example, ConnectU developed a social networking website for college students and alumni, but failed to prevent Mark Zuckerberg from using that idea to develop Facebook, which became the most successful social networking website on the Internet. In contrast, Apple Inc. successfully developed the iPhone and iPad by adding a new knowledge component (i.e., communication function) and rearranging the basic knowledge components of its original idea for iPod. These derivative inventions were not only commercially successful; they also helped prevent others from building on Apple’s original idea for iPod technology.

In order to explain these phenomena, Ahuja et al.’s (2013) introduced generative appropriation (GA) theory. Generative appropriation refers to “a firm’s effectiveness in capturing the greatest share of future inventions spawned by its existing inventions” (Ahuja, Lampert and Novelli, 2013, p. 248). GA theory argues that firms have two general means of increasing their share of future inventions spawned by their existing inventions. First, they can accumulate inventions that build on their prior inventions (i.e., cumulation) and second, they can prevent competitors from doing so (i.e., preclusion). Thus, GA theory brings together two strands of literature – research on path-dependent inventive productivity and research on precluding inventive competition. The former literature on path-dependent inventive productivity suggests that a firm’s existing knowledge not only helps the firm generate predictable outcomes from innovative activities (Levinthal and March, 1981, March, 1991, March and Simon, 1958, Nelson and Winter, 1982); it also facilitates the acquisition and use of new external knowledge components in related areas (Cohen and Levinthal, 1990b). However, overuse of existing knowledge components can lead to the exhaustion of inventive opportunities and dysfunctional rigidity in the firm's technological trajectory (Argyris and Schon, 1978, Dosi, 1988). At the same time, firms often can improve their innovation performance by building on others' knowledge (Katila, 2002, Rosenkopf and Nerkar, 2001). Because such appropriation of ideas by competing firms can cost the focal firm future revenue streams and inventive opportunities, a literature on the preclusion of inventive competition has also emerged. This literature suggests that firms can use defensive mechanisms, such as patent litigation (Graham and Somaya, 2004, Polidoro and Toh, 2011, Somaya, 2003), patent re-examination as keep-out signs (Clarkson and Toh, 2010), and obfuscation (Kim, 2016). Generative appropriation theory contributes to these literatures and warrants separate study by hypothesizing that the path-dependent accumulation of new inventions is inherently linked to the preclusion of competitors' inventions. That is, given a limited supply of inventive opportunities in a technological domain (Dosi, 1988, Kim and Kogut, 1996), the accumulation of inventions by one firm may crowd out inventions by competitors in the same technological domain (Ahuja et al., 2013).

With this study, I empirically test and extend two of Ahuja and colleagues' (2013) untested propositions about the effects of knowledge dispersion on generative appropriation. Specifically, I examine two dimensions of knowledge dispersion - technology dispersion and geographic dispersion. I conceptualize technology dispersion as the degree to which knowledge components are distributed across different inventive domains. I argue that a firm's high technology dispersion may lead to lower generative appropriation of the firm by making it difficult for the focal firm to dominate a narrow knowledge domain and to gain in-depth knowledge in narrow inventive domain necessary to generate cumulative inventions (Ahuja, Lampert and Novelli, 2013). I conceptualize geographic dispersion as the degree to which knowledge components are distributed across geographic locations. I argue that geographic dispersion has a curvilinear influence on generative appropriation. By obfuscating knowledge components, high geographic dispersion can make competitors' expropriation of a focal firm's inventive knowledge more difficult. However, geographic dispersion may also exponentially increase the focal firm's costs of developing cumulative innovations. Thus, when geographic dispersion is very high, exponential cumulative invention costs may offset preclusive benefits and when it is very low the lack of preclusive benefits offset benefits of low invention costs. With a moderate level of geographic dispersion, firms may be able to gain both cumulative and preclusive benefits sufficient to generate valuable cumulative inventions.

Although I borrow Ahuja et al.'s (2013) logic in the development of these hypotheses, I question the efficacy of the underlying theoretical mechanisms and argue that the effects of knowledge dispersion on generative appropriation depend on the availability of technology opportunities. Indeed, the degree of inventive advances is different across industries (Klevorick et al., 1995) and, consequently, a firm's environment can vary in the rate at which opportunities for new inventions become available to inventors (Baysinger and Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995). If the availability of technology opportunities increases rewards for the experimental search for new knowledge components relative to the rewards for recombining well-known knowledge components and technology dispersion provides access to those opportunities, then the availability of technology opportunities in the inventive environment could decrease the negative effects of technology dispersion on a firm's ability to generate derivative inventions. Further, the availability of technology opportunities could make focused, defensive invention less effective in precluding derivative inventions by competitors. Together, these factors suggest that technological knowledge dispersion may not reduce generative appropriation in high technology opportunity environments. Likewise, technology opportunities may weaken the relationship between geographic dispersion and generative appropriation. Increased opportunities for knowledge combination offset R&D coordination costs, but they could also make the defensive use of geographic knowledge dispersion less effective. Consequently, the combination of lower derivative invention costs and lower preclusive benefits may flatten the curvilinear effect of geographic dispersion on generative appropriation.

I test the hypotheses with a sample of 17,866 firm-year observations in manufacturing industries between 1992 and 2006. Results from regression analyses largely support all four hypotheses, although the curvilinear effect of geographic knowledge dispersion appears to be contingent on the availability of technological opportunities. However, a supplementary analysis shows that most of the effects appear to be driven by the focal firm's accumulation of derivative inventions rather than by the preclusion of competitors' inventions. Indeed, I find little evidence that a firm's accumulation of path-dependent inventions crowds out competitors' inventions in similar technological domains.

These results contribute to the literatures on path-dependent inventive productivity and the preclusion of competitive invention. First, in contrast with prior studies that either focus on a firm's own path-dependent inventive productivity or on the preclusion of competitive invention, my study builds on generative appropriation theory to concurrently focus on both. While initial results support generative appropriation theory's propositions about the effects of knowledge dispersion, the supplementary analysis suggests that the study of generative appropriation should often involve independent analyses of path-dependent inventive productivity and preclusion of competitive invention. Future research will need to be done to identify contexts in which a firm's path-dependent inventions meaningfully crowd out competitive invention. Second, my study also contributes to the literature on path-dependent invention by uncovering the moderating effects of technology opportunities on the relationship between a firm's knowledge dispersion and its derivative invention productivity. Finally, I conclude with a discussion of the implications of these findings for practitioners and make recommendations for future research.

4.2. THEORETICAL FRAMEWORK

Generative appropriation (GA) refers to the degree to which a firm captures future inventions derived from its existing inventions (Ahuja, Lampert and Novelli, 2013). When firms generate derivative inventions that build on their existing knowledge and prevent competitors from building on their existing knowledge, they gain higher GA. Following Ahuja et al. (2013), I refer to a firm's derivative inventions that build on its own existing knowledge as cumulation and I refer to a firm's prevention of competitors from building on that same existing knowledge as preclusion.

Generative appropriation theory contributes to the literature by simultaneously considering the roles of cumulation and preclusion. Although scholars have discussed the importance of path-dependent inventive productivity (Cohen and Levinthal, 1990b, Levinthal and March, 1981, March, 1991, March and Simon, 1958, Nelson and Winter, 1982) and preclusion of competitive invention (Clarkson and Toh, 2010, Graham and Somaya, 2004, Kim, 2016, Polidoro and Toh, 2011, Somaya, 2003), few studies bring together the two strands of literature. Prior research on the path-dependent inventive productivity suggests that firms can create more reliable innovations by combining existing knowledge components (Levinthal and March, 1981, March, 1991, March and Simon, 1958, Nelson and Winter, 1982). Indeed, prior empirical studies show that repeated use of prior knowledge may improve innovation performance of a firm (Katila and Ahuja, 2002) and the rearrangement of existing knowledge components without altering core concepts can produce valuable new inventions (Henderson and Clark, 1990). Further, in-depth knowledge about existing inventions may help absorb external knowledge from related areas (Cohen and Levinthal, 1990b). Empirical studies also show that competitors can benefit from building on a focal firm's existing knowledge (Katila, 2002, Rosenkopf and Nerkar, 2001). Indeed, building on others' inventions facilitates new product development and commercialization (Katila 2002; Rosenkopf and Nerkar 2001). In contrast, the literature on the preclusion of inventive competition suggests that a firm can block others from exploiting its inventive domain by using defensive mechanisms, such as patent litigation (Graham and Somaya, 2004, Polidoro and Toh, 2011, Somaya, 2003), patent re-examination (Clarkson and Toh, 2010), and obfuscation (Kim, 2016).

Generative appropriation theory contributes to these literatures by suggesting that a firm's path-dependent invention is inherently linked to its ability to preclude others' competitive inventions. Specifically, GA theory suggests that the offensive accumulation of inventions by one firm may crowd out inventions in the same technological domain by competitors. Given that there are limited inventive opportunities in a technological domain (Argyris and Schon 1978; Dosi 1988; Fleming 2001; Kim and Kogut 1996), firms that build on a particular set of technologies often have to compete to gain better inventive opportunities. When knowledge components are used, the remaining possible combinations of those knowledge components are likely to be less useful (Argyris and Schon 1978). Thus, it is important for a firm to defend its inventive domain from others' competitive inventive efforts. If inventive opportunities are limited within a particular technological domain, then a firm's accumulation of derivative inventions may help preclude competitors from developing derivative inventions based on the firm's older knowledge components (Ahuja et al., 2013). Thus, simultaneous study of both cumulation and preclusion may help better understand the path-dependent invention process of firms.

4.2.1. Technological Knowledge Dispersion and Generative Appropriation

I conceptualize technology dispersion as the degree to which knowledge components are distributed across inventive domains. This conception of technological knowledge dispersion is similar to differently named constructs in previous studies, including technological diversification (Garcia-Vega, 2006, Quintana-García and Benavides-Velasco, 2008) and technological knowledge breadth (Wadhwa and Kotha, 2006). Firms create inventions by combining knowledge components available to them (Fleming, 2001, Levinthal and March, 1993, Nelson and Winter, 1982, Schumpeter, 1939) and firms often begin the invention process by examining familiar knowledge components (Ahuja, 2000). Because diversification of those knowledge components creates opportunities for novel recombinations (Patel and Pavitt, 1997), firms with higher technological knowledge dispersion may be able to experiment with combinations and create more exploratory innovations (Quintana-García and Benavides-Velasco, 2008). However, such combinations of knowledge components from diverse inventive domains may make it difficult for firms to reliably generate inventions (Martin and Mitchell, 1998) because creation and integration process of inventions may require different know-how and greater cognitive effort (Grant, 1999).

I argue that technology dispersion negatively influences generative appropriation. Higher technology dispersion may weaken a firm’s ability to effectively develop multiple cumulative inventions. Developing derivative inventions requires in-depth understanding about the knowledge domain (Ahuja et al., 2013). Because gaining in-depth understanding of knowledge requires intensive learning (Cohen and Levinthal, 1990a), successful cumulative inventions may depend on the amount of experience the firm gains in a core inventive domain (Stuart and Podolny, 1996). Although the combination of diverse knowledge components (i.e., higher technology dispersion) can increase the innovativeness of the firm, difficulties in integration of diverse knowledge components (Grant, 1999) and lower reliabilities associated with such knowledge combinations (Martin and Mitchell, 1998) may require the firm to spend considerable resources during the invention process. Thus, all things being equal, firms that possess technologically dispersed knowledge components are less likely to develop in-depth knowledge about the inventive domains and to reliably develop derivative inventions.

Second, technology dispersion may reduce a firm’s ability to prevent competitors from building on the focal firm’s existing inventions. Although a firm’s dispersion of knowledge components across technical space may also make recombination of those elements more difficult for competitors, such dispersion increases tangential invention opportunities for competitors. This in turn may make it difficult for a firm to dominate in narrow inventive domains and to discourage competitors from invading those domains. In contrast, if a firm focuses on a narrow technological domain, the firm is more likely to develop in-depth knowledge and generate multiple inventions in that domain (Ahuja et al. 2013). Given that there are limited opportunities in an inventive domain (Kim and Kogut, 1996), a firm's accumulation of inventions and its competence in a particular inventive domain should decrease competitors' incentive and ability to invade that domain. For example, Gillette narrowly focused its R&D on a razor technology and generated 22 related patents, including the Sensor Excel and the Sensor 3. This, in turn, discouraged competitors from building on Gillette's innovations and allowed Gillete to dominate in the domain (Rivera and Kline, 2000). In addition to increasing the number of competitive invention opportunities, a firm's technology dispersion may give competitors more time to take advantage of those opportunities. Indeed, integrating diverse knowledge components can lengthen the focal firm's invention processes due to integration difficulties (Quintana-García and Benavides-Velasco 2008). Therefore, I offer the following hypothesis:

Hypothesis 1: An increase in technology dispersion decreases generative appropriation.

4.2.2. Geographic Knowledge Dispersion and Generative Appropriation

In this paper, I conceptualize geographic dispersion as the degree to which knowledge components are distributed across geographic space. Research suggests that firms strategically distribute R&D activities across geographic space to prevent the appropriation of their innovations by competitors (Zhao, 2006). Consequently, strategic geographic dispersion may also influence the generative appropriation of firms. I argue that geographic dispersion may have a curvilinear influence on generative appropriation. To explain the curvilinear relationship, I draw on additive combinations of latent mechanisms suggested by Haans et al. (2015). Specifically, I contend that the difference between increasing preclusive benefits from knowledge fragmentation and exponentially increasing costs for cumulative innovations (i.e., exponential cumulative disadvantages) may lead to the curvilinear relationship (See Figure 4.1 for graphical representation).

In contrast to my theory about the effect of technology dispersion, I argue that geographic dispersion of inventive knowledge components helps preclude competitors from building on a focal firm's technology. In the case of technology dispersion, I argue that technically diverse knowledge components may increase the complexity of competitors' efforts to recombine the focal firm's existing knowledge components, but they also increase others' opportunities to combine those existing knowledge components with new knowledge components, and that the latter mechanism is stronger than the former. In the contrasting case of geographic dispersion, I argue that the primary mechanism of preclusion is the obfuscation of existing knowledge components and that geographic dispersion does not increase the opportunities for combining existing knowledge with new knowledge in the way that technological dispersion does. Thus, knowledge fragmentation across different geographic locations can may make it more difficult for competitors build on the focal firm's invention. Even though proprietary technical knowledge tends to spill over and become fully disclosed to competitors over time (Almeida and Kogut, 1999, Jaffe et al., 1993), knowledge spillover often requires close interactions (Bell, 2005) or the employment of competitors' scientists or inventors (Almeida and Kogut, 1999, Rosenkopf and Almeida, 2003), both of which can be enabled by geographic proximity. Further, focal firm can distribute complementary knowledge components over multiple geographic locations and doing so makes it difficult for competitors to build on the focal firm's inventions (Ahuja, Lampert and Novelli, 2013). Thus, tapping into knowledge components dispersed across multiple locations may require competitors to expend more time and effort on invention, and therefore, provide a lead time advantage to the focal firm (Lieberman and Montgomery, 1998).

In contrast, geographic dispersion may impair cumulative invention by a focal firm. Communication and coordination among R&D units in different geographic locations increase the cost of cumulative invention. As the number of R&D units (n) in different geographic locations increases, the hypothetical one-to-one communication channels among them rises to $n(n-1)/2$. Although in most cases each R&D unit would not be required to coordinate with all other R&D units, the communication and coordination among R&D units would – on average – become exponentially more complex and costly. In addition, as different R&D units develop distinct knowledge components (Lahiri, 2010), the dispersion of R&D resources across multiple locations may lead to the development of multiple, unique knowledge components. However, such a dispersion of R&D resources could produce diverse but shallow knowledge in each unit rather than in-depth knowledge in related domains (Lahiri, 2010).

Together, these effects on the preclusive and cumulative components produce the overall hypothesized relationship. When geographic dispersion is lower, firms may have difficulty precluding competitors from building on the focal firm's inventions. Although firms with low geographic R&D dispersion may efficiently generate cumulative inventions, competitors' enhanced ability to build on the focal firms' inventions would offset the benefit of lower R&D costs. When a firm's knowledge is distributed over a small number of R&D locations, each R&D location of the firm is more likely to include a set of complementary knowledge components. Consequently, proximate competitors may find it easier to effectively expropriate and those knowledge components. Thus, higher cumulative innovations of the focal firm in this case might provide more competitive invention opportunities.

When geographic dispersion is very high, competitors may have difficulty in tapping into complementary resources across diverse geographic locations to build on the focal firm's inventions. Further, tapping knowledge components across diverse geographic locations may take longer time than the components dispersed across fewer geographic locations. Given that the value of knowledge resources depreciates over time (Argote, 2012), competitors may have lower incentive to build on the focal firm's inventions. However, complexities in organizational R&D activities and exponentially increasing coordination costs may overwhelm the preclusive benefits of high geographic dispersion (See Figure 4.1 for graphical representation). Thus, such increasing coordination costs may hinder cumulative inventions of the focal firm. Although geographic dispersion may prevent others from building on the focal firm's inventions, higher coordination costs and complexities that exponentially increases with geographic dispersion may make it also difficult for the focal firm to build on its own prior knowledge.

In contrast, a moderate level of geographic knowledge dispersion may help firms balance the preclusive and cumulative components. A moderate number of geographic R&D units would enable R&D units of a firm to coordinate efficiently while keeping the complexity of R&D activities lower; at the same time, firms may be able to distribute complementary knowledge components over diverse geographic locations, thereby, lowering expropriation from competitors. That is, firms with a moderate level of geographic dispersion may be efficient in both generating cumulative inventions and in preventing others from doing so. Thus, the net effect may lead to higher generative appropriation. We, therefore, hypothesize:

Hypothesis 2: Geographic dispersion has a curvilinear (Inverted U-shape) relationship with generative appropriation, such that a firm's moderate geographic dispersion leads to higher generative appropriation than high or low geographic dispersion.

The previous two hypotheses highlight the influences of a firm's knowledge dispersion on generative appropriation. In developing the next two hypotheses, I argue that a munificence of technology opportunities in the firm's environment moderates the influences of knowledge dispersion on generative appropriation. Technology opportunity – the availability of inventive advances – varies across industries (Baysinger and Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995). For example, the computer device and pharmaceutical industries have higher rates of innovation than the footwear industry. Differences in technology opportunity across industries can be attributed to inherent characteristics of an industry's technology and to the ongoing enhancement of scientific understanding (Klevorick, Levin, Nelson and Winter, 1995). In industries with higher technology opportunity, R&D is more likely to generate valuable inventions. Further, experimental search may be more likely to generate valuable inventions in high technology opportunity areas (Baysinger and Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995, Uotila et al., 2009) because the core knowledge of a firm may become obsolete relatively quickly in those areas (Sørensen and Stuart, 2000).

4.2.3. Technology Opportunity and Technology Dispersion

In my development of Hypothesis 1, I point out that high technology dispersion weakens a firm's ability to efficiently generate derivative inventions. I also contend that high technology dispersion weakens a firm's ability to prevent others from generating derivative inventions based on the focal firm's inventions. Here, I argue that these relationships might not hold up when the availability of technology opportunity is higher. Specifically, I argue that the availability of technology opportunity reduces the negative effects of technology dispersion on generative appropriation.

The availability of technology opportunity may make it less efficient for focal firm to create valuable cumulative inventions in narrow domain (i.e., lower technology dispersion). In high technology opportunity areas, the value of a firm's core knowledge often erode more quickly (Sørensen and Stuart, 2000) while experimental search often results in the creation of valuable inventions (Baysinger and Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995, Uotila, Maula, Keil and Zahra, 2009). Thus, a firm's focus on narrow inventive domains may hinder the focal firm's creation of valuable derivative inventions over time.

The availability of technological opportunities may also make it difficult for a firm to preclude competitors from building on its own inventions. All things being equal, as the number of technology opportunities increases, the resources required to identify and exploit all those opportunities are likely to increase. Indeed, increasing technology opportunity would make it more difficult for a firm to anticipate and prevent competitors from combining the firm's existing knowledge with new knowledge components. Consequently, a firm's competence in a narrow inventive domain may not guarantee the firm's dominance in a domain where the value of existing inventions erodes quickly. This implies that competitors may have greater incentive to build on the focal firm's inventions in narrow inventive domains that are characterized by high technology opportunity. Therefore, given that both cumulative and preclusive components of the focal firm with low technology dispersion are weakened in high technology opportunity areas, I hypothesize:

Hypothesis 3: An increase in technology opportunity reduces the negative effect of technology dispersion on generative appropriation.

4.2.4. Technology Opportunity and Geographic Dispersion

In my development of Hypothesis 2, I suggest that geographic dispersion has an inverted U-shaped relationship between geographic dispersion and generative appropriation. I argue that the geographic dispersion of knowledge components helps preclude competitors from building on a firm's inventions, but that exponentially increasing R&D coordination costs overwhelm this preclusive benefit at high levels of geographic dispersion. Here, I argue that technological opportunities weaken the overall curvilinear relationship between geographic dispersion and generative appropriation.

The availability of technology opportunities may decrease the negative effect of geographic dispersion on the cumulative development of related inventions. Technology opportunity reflects a munificence of viable, potential knowledge combinations (Baysinger and

Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995). Indeed, as previously noted, the availability of technology opportunity may increase the value of experimental innovative efforts (Baysinger and Hoskisson, 1989, Klevorick, Levin, Nelson and Winter, 1995). Because isolated R&D units tend to develop distinct bodies of knowledge (Lahiri, 2010), unique knowledge from geographically dispersed R&D units may become a knowledge pool for novel cumulative inventions in high-opportunity environments. In such cases, novel recombination opportunities might offset the disadvantages of thin knowledge resource allocation across geographically dispersed R&D units. That is, some of the coordination costs may be offset by experimental recombination opportunities from distinct knowledge components as geographic dispersion increases.

The availability of technology opportunities may also weaken a firm's ability to preclude competitors from building on its inventions. Although geographic dispersion of knowledge components can make it difficult for competitors to tap into them, competitors may find it easier to discover and combine new knowledge components with existing subsets of components in high technological opportunity environments. Thus, in high technological opportunity environments, competitors may still have a relatively higher incentive to build on a focal firm's knowledge components.

Together, the effects of technology opportunities should moderate the curvilinear relationship between geographic knowledge dispersion and GA. When technology opportunities increase, it should become more difficult for a firm to preclude competitors from building on its existing inventions. Further, increasing technology opportunities should increase the productivity of a focal firm's efforts to combine new knowledge components with existing components, which in turn should offset some of R&D coordination costs that geographic dispersion increases. In sum, the combination of lower R&D coordination costs and greater difficulty in precluding competitors from building on existing inventions suggests that the availability of technological opportunities weakens the curvilinear relationship between geographic dispersion and GA. Therefore, I hypothesize:

Hypothesis 4: Technological opportunities reduce the curvilinear influence of geographic dispersion on generative appropriation.

4.3. METHODOLOGY

4.3.1. Sample and data

I constructed my sample using the 2006 NBER Patent database, the Patent Network Dataverse database (Lai et al., 2011), and Standard and Poor's Compustat. I first identified public U.S. firms using the Standard and Poor's Compustat. My sample consists of publicly traded U.S. manufacturing firms (SIC 200 – 399) that existed between 1992 and 2006. Manufacturing industries offer a useful context for my study because invention and the protection of intellectual property often play important roles in determining the performance of manufacturing firms. Indeed, U.S. manufacturing industries represented 12 percent of U.S. GDP in 2012, but conduct 69% of R&D (National Science Foundations, 2015). Moreover, manufacturing firms primarily patent their technologies to protect them from imitation (Cohen et al., 2000). Consequently, multiple prior studies use patents as a proxy for inventiveness of the manufacturing firms (Hall et al., 2005, Mudambi and Swift, 2014, Uotila, Maula, Keil and Zahra, 2009). To be included in the sample, firms also had to have at least one citation during the observation period to patents from the previous six years so that GA can be measured. I use citation information from Patent Network Dataverse data (Lai, D'Amour, Yu, Sun and Fleming, 2011). Excluding firm-year observations without citations or missing data from Compustat, I are left with a final sample of 2,615 firms and 17,866 firm-year observations.

Variables

Dependent variable Generative appropriation is a firm level construct that embodies a firm's share of inventions that build on the firm's prior knowledge. In contrast to invention-related measures of exploitation that capture the proportion of a firm's total inventions that build on the firm's prior inventions (Katila and Ahuja, 2002, Tzabbar and Kehoe, 2014), generative appropriation captures the extent to which a firm creates inventions in its own inventive domain (i.e., self-citations) relative to others (i.e., others' citations to the focal firm's prior inventions). Figure 4.2 illustrates the generative appropriation concept using patent citations as a proxy for knowledge flow. In the figure, the focal firm has two patents - patent A and patent B. If the focal firm's patent A was cited by patent E of competitor 1 and by patent D of competitor 2 while the focal firm's patent B was cited by patent D of competitor 2 and patent C of the focal firm, then the focal firm appropriates 25% of its future innovations spawned by its previous patents A and B.

Consistent with the figure, I measure generative appropriation using forward citations of patent applications that were eventually granted. Patents are a good proxy for firm invention because patent citations indicate knowledge flow (Jaffe and Trajtenberg, 2002, Jaffe, Trajtenberg and Henderson, 1993). Thus, citation information from future patents to prior art captures how future inventions build on prior knowledge. Following Ahuja et al.'s (2013) suggestion, I operationalize generative appropriation as the proportion of self-forward citations to total forward citations made at time *t* – 0 to the focal firm's patents applications filed between t – 6 and t – 1:

$$\textit{Generative Appropriation} = \frac{\textit{Self-citations made by focal firm } t-0 \textit{ to focal firm patents } t-1 \textit{ to } t-6}{\textit{Total citations } t-0 \textit{ by all including focal firm to focal firm patents } t-1 \textit{ to } t-6}$$

I use a six-year window because prior studies show that most of the value of knowledge resources depreciates within four to five years (Argote, 2012) and that most patent citations occur within six years after a patent was filed (Jaffe, Trajtenberg and Henderson, 1993, Katila, 2002, Smith et al., 1991). I checked the robustness of my results with four-year and five-year windows and the results from these analyses were qualitatively similar. Following accepted practice for the use of proportional dependent variables, I transform the generative appropriation variable using a logit function (Greene, 2003, Yang et al., 2010). The transformed variable is equal to ln(generative appropriation /(1 – generative appropriation)). Because this transformation is not defined when generative appropriation is equal to one or zero, I use 0.9999 and 0.0001 in such cases, respectively.

Independent and moderating variables All independent variables, moderating variables, and innovation-related control variables are measured between t – 6 and t – 1 (See Figure 4.2). Because my dependent variable captures how much a firm builds on its prior knowledge and prevents others from doing so, I control for the characteristics of the prior knowledge that is created during the same period (i.e., t – 6 and t – 1).

Consistent with prior studies of technological diversity (e.g., Garcia-Vega, 2006, Hall et al., 2001), I measure technology dispersion using an inverse Herfindahl index of USPTO technology classes of a firm's patents. Specifically, I operationalize technology dispersion as follows:

$$Technology\ dispersion\ t\text{ - }1\ to\ t\text{ - }6\ = 1 - \sum_{i=1}^{n} P^2_{i,\, t-1\ to\ t-6}$$

where P_i is the share of patent applications in USPTO patent class i over the total number of patent applications a firm files between t – 6 to t – 1. This variable ranges between zero and one, and a larger value of this measure indicates that a firm has more diversified technologies.

I measure geographic dispersion in a similar manner. However, instead of patent class information, I use geographic location information in USPTO patent applications. I use state information for U.S. locations and country information for other places (Lahiri, 2010, Singh, 2008). This measure is contingent upon the number of locations and measured using patent applications between t – 1 and t – 6. Like the technology dispersion variable, this variable ranges between zero and one, and a larger value indicates greater geographic dispersion of a firm's inventive knowledge.

I measure technology opportunity following previous studies (Alnuaimi and George, 2015, Yang, Phelps and Steensma, 2010). I use the number of patent applications in a patent class in a year as a proxy for technology opportunity in the inventive domain (Patel and Pavitt, 1997). First, I define technology opportunity for a year (*T*) and then I use the six-year average value of this variable (*T*) because I are interested in the focal firms' prior knowledge between t – 6 and t – 1. I operationalize variable *T* as follows:

$$T\ t\text{ - }n\ = \sum_{j=1}^{J} (patent\ applications_{jt-n} \times P_{ji\ t-n})$$

where patent applications *j* is the number of universal patent applications in USPTO patent class j and P_{ji} is the proportion of the firm *i*'s patent applications in patent class *j* in that year. The number of patent applications in patent class j shows how much technology opportunity exists in the patent class and P_{ji} indicates the proportional importance of the patent class to the focal firm. Values for all patent classes of a firm *i* are summed to calculate *T*. I then average *T* values across six years and divide by 1000:

$$Technology\ opportunity\ t-6\ to\ t-1\ = (Average\ of\ T\ between\ t-6\ and\ t-1)/1000$$

Control variables I control for multiple characteristics of the firm and the environment. I control for the firm's number of patents (i.e., patent stock) because a larger knowledge stock developed by a firm may serve as a good source for recombination (Kogut and Zander, 1992) and, therefore, may enhance cumulative inventions. I use the number of patent applications between t – 6 and t – 1 and use the natural log of this variable to correct for skewness. I control for the resources that are available for firm innovation by including a variable - R&D intensity - equal to R&D expenses divided by total assets at t – 1. I also control for search scope because new knowledge components may affect a firm's cumulative inventions. First, I calculate proportion of new citations in a year (*NC*) between t – 6 and t – 1 and use the average value of the variables:

$$NC\ t-n = \frac{\textit{Citations made at t -n and not used between t-n-1 and t-n-5}}{\textit{total citations made by the focal firm t-n}}$$

I use the focal firm's new citations over the previous five years as a proxy for new knowledge components (Katila and Ahuja, 2002). I operationalize this variable as the six-year average (i.e., t – 1 to t – 6) of the proportion of citations at t – n that were not used in the previous five years to total citations:

$$\textit{Search Scope}\ t-6 \text{ to } t-1 = \textit{Average of NC between } t-1 \textit{ and } t-6$$

I also control for leverage. Leverage may reduce a firm's strategic flexibility (Greve, 2003) and may increase firm's reuse of previous knowledge components. I operationalize leverage as the ratio of long term debt to total assets at t – 1. Because firm performance influences firm search behavior in the innovation process (Greve, 2003), I control for firm performance using sales growth – the increase of sales at t – 0 relative to sales at t – 1. I control for firm size because firm size may influence the scope and scale of a firm's technological search behavior (Yayavaram and Chen, 2015). I measure firm size using the natural log of total assets at t – 1. I control for a firm's product market diversification because such diversification can draw resources away from R&D and promote a culture that avoids the risks associated with R&D (Hitt et al., 1997). Consequently, firms with high diversification may be less engaged in cumulative innovations, which requires long-term commitment in a narrow inventive domain. I include an entropy measure of product diversification (Palepu, 1985). I operationalize this variable as $P_i \ln(1/P_i)$, where P_i is the share of *i* segment (SIC 3 digit) in total sales of a firm at t – 1.

It is particularly important to control for technology complementarity of firms. The value of a firm's technology often depends on other complementary technologies. In such cases, a firm can benefit when others build on its technology to create a supportive technological ecosystem (Alexy et al., 2013, Dodgson et al., 2007, Garud and Rappa, 1994). Thus, based on prior, validating studies (Makri et al., 2010, Ziedonis, 2004), I control the extent to which patents of the focal firm rely on related technologies by including a variable that captures citations to patents in the same NBER sub-category but in different patent classes. To create this variable, I calculated a firm's level of reliance on complementary technology in patent class k in year t - n as follows:

$$K_{t-n,k} = \frac{\text{Number of complementary citations made by all patents in class } k_{t-n}}{\text{Number of patents in class } k_{t-n}}$$

The complementary citations are citations by all patents in patent class *k* to other patents in the same NBER sub-category but in different patent classes in year t - n. I scale this value by the number of all patent applications in the patent class *k* in year t - n. Then, I weight this value (*K*) by the proportion of patents the focal firm files in the patent class *k* at t – n and sum the proportions from all the classes of the focal firm to calculate the importance of technology to focal firm at t – n as shown below:

$$TC_{i,\,t-n} = \sum q_{i,\,t-n,\,k} \times K_{t-n,\,k},$$

where $q_{i,\,t\text{-}n,\,k}$ is the proportion of patents in each patent class *k* possessed by firm *i* at t – n. Because I measure technology variables between t – 1 and t – 6, I use average value of complementary technology between t – 1 and t – 6 as follows:

$$\textit{Technology Complementarity}_{\,t-6 \text{ to } t-1} = \textit{Average of TC between } t-6 \textit{ and } t-1$$

The complexity of the technological environment can also influence firms' ability to build on prior inventions (Sorenson et al. 2006). Complexity reflects the interdependencies among domains in which a firm conducts technological search and invention. To measure this variable, I draw on the NK innovation landscape concept as widely used in management studies (e.g., Ethiraj and Levinthal, 2004, Levinthal and Warglien, 1999, Nickerson and Zenger, 2004, Rivkin, 2000). Following previous studies (Fleming and Sorenson, 2001, Yayavaram and Chen, 2015), I measure interdependence as the number of distinct technology subclasses listed together with a focal patent subclass in patent applications during the previous 10 years. I divide this value by the total number of patents in the focal technology subclass during the same period as followings:

$$E_{t-n,\,k} = \frac{\textit{count of classes previously combined with subclass } k_{\,t-n-10 \text{ to } t-n-1}}{\textit{count of previous patents in subclass } k_{\,t-n-10 \text{ to } t-n-1}}$$

Then, I weight this value by the proportion of patents the focal firm files in the domain at t – n and sum the proportions from all the classes of the focal firm to calculate the complexity in focal firm's environment at t – n:

$$C_{i,\, t-n} = \sum q_{i,\, t-n,\, k} \times E_{t-n,\, k},$$

where q_i, t-n, k is the proportion of patents in each technology class k possessed by firm *i* at t – n. Because I measure technology variables between t – 1 and t – 6, I use average value of complexity between t – 1 and t – 6 (6-year average of $C_{i,\, t-n}$, where n = 1 to 6).

Technology Complexity t – 6 to t – 1 = Average of C between t – 6 and t – 1

Finally, I include year dummies to control for year effects. In my random effects regression, I also include SIC three-digit dummies to control for industry effects.

4.3.2. Model

I analyze firms' technological search and multiple cumulative innovations at different points in time over a fifteen-year period from 1992 to 2006. To account for unobserved heterogeneity and potential autocorrelation problems, which are commonly found in panel data, I employ fixed effects regression. As a robustness check, I employ random effects regression with a pre-sample fixed effect variable equal to the prior ten-year average of generative appropriation (GA) (Bettis et al., 2014, Blundell et al., 1995, Blundell et al., 1999) with industry fixed effects (SIC three-digit dummies). To deal with potential heteroscedasticity problems, I clustered standard errors by firms. The fixed effects regression and random effects regression produce similar results.

4.4. RESULTS

Table 4.1 reports the descriptive statistics and pairwise correlations for all variables. The high correlations between technology dispersion and number of patents (0.64), between technology dispersion and firm size (0.54), and between number of patents and firm size (0.71) suggest that multicollinearity could be a problem. Research suggests that the use of residual-based variables in lieu of raw variable can effectively address potential problems associated with high correlations and endogeneity concern among the raw variables (e.g., Kaul, 2012). We, therefore, created residual-based variables from fixed-effects models that predict the raw variables and used them for my analyses. Specifically, for technology dispersion, I used residuals from a fixed effects regression that predicts technology dispersion as a function of the number of patents and firm size. Likewise, for the number of patents, I used residuals from a fixed effects regression that predicts the number of patents as a function of firm size. I included year dummies and clustered standard errors by firms in both regressions.

Models 1, 2, 3, 4 and 5 in Table 4.2 report the results of fixed-effects regression analyses and Model 6 and 7 report the results of an additional robustness test using random-effects regression. I checked multicollinearity in my model and the variance inflation factor (VIF) for model 5 with standardized variables ranges between 1.01 and 3.02 with an average of 1.57. When I used original variables rather than residuals in my analyses, VIF for Model 5 with standardized variables ranges between 1.01 and 3.79 with an average of 1.69. Thus, the residual approach alleviates multi-collinearity concerns and VIF tests suggest that, in general, multicollinearity is not an issue for my analyses.

Model 1 in Table 4.2 is the baseline model with only control variables. Model 2 reports the results of the tests of Hypotheses 1 and 2. Hypothesis 1 suggests that an increase in technology dispersion decreases GA. The statistically significant, negative coefficient on the technology dispersion variable in Model 2 (β=-1.162, p =0.000) confirms the negative effect of technology dispersion on GA. Thus, the data support Hypothesis 1. Figure 4.3 illustrates the relationship between technology dispersion and GA.

Hypothesis 2 suggests that geographic dispersion has an inverted-U shaped curvilinear relationship with GA. To test hypothesis 2, I introduce the first-order and second-order geographic dispersion variables in Model 2. To check whether the inclusion of the second-order geographic dispersion variable significantly improves the statistical fit of the model, I compare the R-square statistic of Model 2 to that of a similar model without the second-order variable. The model with the second-order geographic dispersion variable provides a significantly better fit to the data than the model without the second-order variable (p value = 0.0013). The coefficients in Model 2 on the first-order geographic dispersion variable (β=0.738, p =0.254) and its squared term (β=-1.828, p =0.027) indicate an inverted-U shaped curvilinear relationship. However, further analysis of Model 2's results show that the inflection point - before and beyond which geographic dispersion is associated with lower GA – is 0.202. This value is more than one standard deviation below the mean of geographic dispersion, as shown in Figure 4.4. This indicates that firms' lower level geographic dispersion leads to higher GA. Although the results suggest a curvilinear relationship, I cannot confirm that relationship. I conduct Fieller's significance test of the inverted-U relationship (Haans et al., 2015), and it does not confirm the curvilinear relationship (p=0.127). Thus, these results only partially support Hypothesis 2. Figure 4.4 illustrates the overall relationship between geographic dispersion and GA.

Hypothesis 3 proposes that an increase in technology opportunities reduces the negative effect of technology dispersion on GA. In Models 3 and 5, I introduce the interactions between technology dispersion and technology opportunities to test Hypothesis 3. Both coefficients for the interaction term between technology dispersion and technology opportunities in Model 4 (β =0.763, p=0.007) and in Model 6 (β =0.915, p=0.002) indicate that the interaction between the two variables has a positive effect on GA. To better understand the interaction effects, I plot the relationship in Figure 4.5, using ± 1 standard deviation (SD) from the mean of technology opportunities. As shown by coefficient on the interaction between technology dispersion and high technology opportunities (+1 SD), high technology opportunities weaken the negative effect , supporting Hypothesis 3.

Hypothesis 4 proposes that an increase in technology opportunities reduces the curvilinear effect of geographic dispersion on GA. In Models 4 and 5, I introduce the interaction terms between geographic dispersion and technology opportunities to test Hypothesis 4. The coefficients for interaction between geographic dispersion and technology opportunities in Model 4 (β =-1.780, p=0.006) and for the interaction between squared term of geographic dispersion and technology opportunities in Model 4 (β =1.780, p=0.033) indicate that the relationship between geographic dispersion and GA might change in the presence of more technology opportunities. Likewise, the coefficients in Model 5 for the interaction between geographic dispersion and technology opportunities (β =-2.047, p=0.002) and for the interaction between the squared term of geographic dispersion and technology opportunities (β =1.982, p=0.018) show similar results. To illustrate this interaction effect, I plot the relationship in Figure 4.6. The results of Model 5 suggest that, at one standard deviation below the mean of technology opportunities, the inflection point in the relationship between geographic dispersion and GA is 0.376. Compared with inflection point in Figure 4.4 (0.202), the extreme point in Model 6 is close to mean (0.40). I conduct Fieller's significance test of the inverted-U relationship (Haans et al.'s, 2015) and the results support the curvilinear relationship (p=0.002). Therefore, Hypothesis 4 is supported.

Models 6 and 7 in Table 4.2 report the results of random-effects regressions. Because my sample consists of multiple manufacturing industries, I check the robustness of my results with industry fixed effects in the random-effects regressions. I also use pre-sample fixed effects equal to the ten-year pre-sample average of GA to alleviate unobserved heterogeneity (Bettis et al.

2014; Blundell et al. 1995, 1999). The results from the random effects regression are substantively similar to the results of the other regressions. Additional robustness tests with varied dependent variable windows (i.e., four and five years), a lagged dependent variable approach, and fixed effects regression with the original variables rather than the residual-based variables also show similar results.

4.4.1. Supplementary analyses

Given the proportional nature of GA, I conduct a supplementary analysis to examine two theorized mechanisms. First, I are interested in distinguishing the effects of knowledge dispersion and technological opportunity on a firm's effectiveness in developing derivative inventions from their effects on others' effectiveness in developing derivative inventions. Second, I are interested in the influence of inventive crowding out – the degree to which a firm's derivative inventions preclude others from developing derivative inventions. I explore these issues with two sets of regressions on 1) others' citations of the focal firm's inventions and 2) self-citations. This analysis culminated in regressions that include all the dependent variables from the analysis summarized in Model 5 of Table 4.2 plus lagged measures of others' citations and self-citations. More constrained models do not qualitatively alter the results of the supplementary analysis. In Table 4.3, I report the results of my supplementary analysis.

The dependent variable of Model 1, Table 4.3 is others' citations to the focal firm's prior patent applications, which is indicative of a firm's effectiveness in precluding others from building on its prior inventions. As shown in Model 1, technology dispersion decreases others' citations (β= -0.365, p value = 0.000). None of the other coefficients on the dispersion-related variables is statistically significant. These results challenge the logic behind the hypotheses. I argued that technology dispersion may make it easier for competitors to build on the focal firm's inventions. In contrast, these results indicate that when technology dispersion is higher, competitors' building on the focal firm's inventions is lower. I also find no evidence of inventive crowding out.

In contrast, Model 2 of Table 4.3, in which self-citations serve as the dependent variable, mirrors Model 5 of Table 4.2. The coefficient on the technology dispersion variable in Model 2 is negative and statistically significant (β= -0.764, p value = 0.000) and the coefficient on the interaction between technology dispersion and technology opportunity is positive and significant

(β= 0.356, p value = 0.000). This result suggests that technology dispersion generally decreases self-citations, but that the availability of technological opportunities reduces the negative influence of technology dispersion. I also find that the coefficients on the geographic dispersion-related variables are similar to those in Model 5 of Table 4.2. The coefficient on the geographic dispersion variable is positive and significant (β=0.671, p value=0.002) and the coefficient on the geographic dispersion-squared is negative and significant (β=-0.663, p value=0.028). The coefficient on the interactions between geographic dispersion and technology opportunity is negative and significant (β=-0.578, p value=0.000) and the coefficient on the interaction between geographic dispersion-squared and technology opportunity is positive and marginally significant (β=0.383, p value=0.064). Consistent with the logic behind my hypotheses, these results suggest that inverted U-shape relationship with self-citation that tends to dissipate as technology opportunity increases. Model 2 also shows some evidence of reverse inventive crowding out in which others' appropriation of a focal firm's ideas may discourage the focal firm from continuing to build on its original ideas. Indeed, citations from others to a firm's prior inventions at t – 1 is negatively associated with self-citations of focal firm at t – 0 in Model 2 (β=-0.033, p value=0.006).

4.5. DISCUSSION

The concept of generative appropriation contributes to the broader literature on appropriation. Much of the previous research on appropriation focuses on how firms capture financial value from their existing inventions (Hall, Jaffe and Trajtenberg, 2005, McGahan and Silverman, 2006, Teece, 1986). Research on inventive exploitation examines the causes and effects of a firm reusing familiar ideas (e.g., Choi and McNamara, 2017, Katila and Ahuja, 2002, Tzabbar and Kehoe, 2014). Other studies highlight the ways that a firm can preclude others from appropriating the value in its prior inventions (Clarkson and Toh, 2010, Graham and Somaya, 2004, Kim, 2016, Polidoro and Toh, 2011, Somaya, 2003). Ahuja et al.'s (2013) theory of generative appropriation contributes to this literature by arguing that a firm's accumulation of inventions that build on its prior inventions is inherently linked to the firm's ability to preclude others from building on those same prior inventions. Given this gap in the literature and the possibility that generative appropriation helps firms sustain competitive advantage, I empirically test and extend some of Ahuja et al.'s (2013) propositions about the effects of knowledge dispersion on generative appropriation.

In support of Hypothesis 1, my findings suggest that higher technological knowledge dispersion of firms generally leads to lower generative appropriation. In my development of Hypothesis 1, I speculate that technological knowledge dispersion makes invention that builds on prior inventions less efficient. I also argue that technological dispersion of a firm's prior inventions creates opportunities for others to build on those prior inventions. I empirically test these theoretical mechanisms with my supplementary analysis and find evidence that the negative relationship between technological dispersion and generative appropriation is driven by the effect on the firm's ability to build on its own inventions rather than the effect the firm's preclusion of others' competitive inventions.

In support of hypothesis 2, evidence from Model 2 of Table 4.2 suggests that geographic knowledge dispersion has a curvilinear relationship with generative appropriation. However, further analysis of the resulting function's curvilinearity cannot confirm a truly inverted-U shape relationship. This suggests that geographic dispersion leads to exponentially increasing R&D costs and decreasing derivative inventions for the focal firm. However, in contrast with my logic for Hypothesis 2, this also suggests that geographic dispersion may not generally make building on the focal firm's inventions much more difficult for competitors. That said, results depicted in Model 5 of Table 4.2 and in Figure 4.6 seem to suggest that geographic might have some preclusive effect when technological opportunities are low. I also examine results depicted in Table 3 and find little evidence that geographic dispersion precludes competitive derivative inventions. Once again, it appears that the primary mechanism linking knowledge dispersion to generative appropriation is the focal firm's effectiveness in producing inventions that build on its own inventions.

In support of Hypotheses 3 and 4, I also find evidence that technology opportunities weaken the relationships between knowledge dispersion and generative appropriation. This suggests that the availability of technological opportunities could make a firm's integration of its existing knowledge components less important during the subsequent development of inventions. Instead, technology opportunities may promote experimental recombination and, in doing so, reduce the influence of knowledge dispersion on the cumulative component of generative appropriation. It may also imply that technological opportunities make the preclusion of others' competitive inventions more difficult; however, my supplementary analysis suggests that the results are mainly driven by the effects on a firm's own inventive productivity rather than by the effects on its preclusion of others from building on its prior inventions.

To the best of my knowledge, this study is the first to empirically examine the antecedents of generative appropriation. As such, its findings contribute to the literature on knowledge search and appropriation. Drawing on the concepts of search behavior (March and Simon, 1958, Nelson and Winter, 1982), scholars have extensively studied path dependent invention. This study contributes to this stream of literature by paying attention to how both a focal firm and its competitors concurrently search to build on the focal firm's inventions. my findings show that strategic modification of knowledge dispersion helps firms create a larger share of derivative inventions spawned by their existing inventions relative to competitors' share. Indeed, future studies on search behavior and invention should pay more attention to competitive dynamics. For example, future studies could examine whether previous study results hold up when competitors' search behaviors are simultaneously considered.

Although I generally find support for my hypotheses, the supplementary analysis suggests that knowledge dispersion has greater influence on the focal firm's effectiveness at building on its prior inventions than on others' effectiveness at building on the same prior inventions. Moreover, I find little evidence of inventive crowding out in which a firm's accumulation of derivative inventions blocks competitors from building on the same set of knowledge. For academics, this begs questions about the usefulness of the generative appropriation concept. If the cumulative and preclusive components of generative appropriation are not inherently linked through inventive crowding out, then researchers should unpack generative appropriation and conduct separate analyses on its subcomponents. For practitioners, these findings suggest that other means of precluding competitive invention - patent litigation (Graham and Somaya 2004; Polidoro and Toh 2011; Somaya 2003), patent re-examination (Clarkson and Toh 2010), and obfuscation (Kim 2014) – may be more effective than inventive crowding out.

4.5.1. Limitations and Future Research

Future research could intensify the search for inventive crowding out by examining the moderating effects of firm characteristics and environmental conditions. Controlling for technological complementarity of firms' prior inventions and the technology complexity of the environment in this study should make isolating the inventive crowding out effect easier. However, in the interest of generalizability, I study manufacturing firms from a broad set of industries. It is possible that some industries are more prone to inventive crowding out than others and that this sample is too broad to isolate the crowding out effect.

Future study can also examine when citations by others are more valuable and when they are not. The generative appropriation perspective considers forward citations by other players as knowledge spillover and a failure to appropriate value from initial ideas. However, preventing knowledge spillover might be not always beneficial to the focal firm. For instance, Hall et al. (2005) show that an extra forward citation per patent increases market value of the firm owning the patent by 3%. Indeed, knowledge spillover can result in the development of ideas that beneficially spill back to the focal firm (Yang et al. 2010). Likewise, a high proportion of self-forward citations might prevent industry peers from generating complementary technologies and infrastructure for the focal firm's technology (Alexy, George and Salter, 2013, Harhoff, 1996). Consequently, the focal firm might not be able to maximize end user value or legitimacy of the initial innovation. Thus, future research should examine how firm characteristics, technological characteristics, and industry characteristics affect such conditions.

4.5.2. Implications

I conclude by suggesting implications for managers and practitioners. My findings indicate that firms may be able to devise their knowledge dispersion strategies in a way that increases generative appropriation when they are committed to multiple cumulative innovations. A firm's ability to modify knowledge dispersion may be limited because alteration of knowledge dispersion, particularly technological knowledge dispersion, takes a long-time and may involve considerable costs. However, because cumulative innovations also take place over long periods of time, firms may be able to influence generative appropriation through their geographic and technological knowledge dispersion strategies (Ahuja et al. 2013). However, as my findings indicate, such strategies might not hold up in high technology opportunity environments. Further, my findings are mainly driven by a firm's efficiency in creating cumulative inventions. Therefore, managers and practitioners need to be careful in determining whether those strategies are available and how they will implement them together with other defensive mechanisms such as patent litigation, patent re-examination, and obfuscation. Indeed, defensive mechanisms themselves may be sufficient only to protect a firm's inventive domains but expanding the inventive domains may require the firm to enhance its cumulative component. Managers and practitioners should carefully consider how to allocate their resources to cumulative and preclusive mechanisms to optimize their benefits from innovative activities.

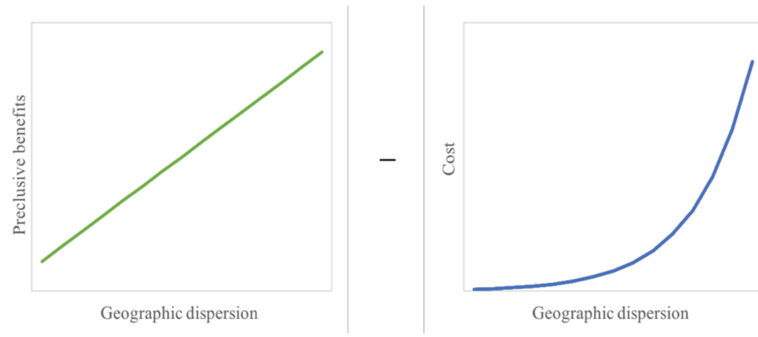

Figure 4.1. Net Effect of Preclusive Benefits and Costs

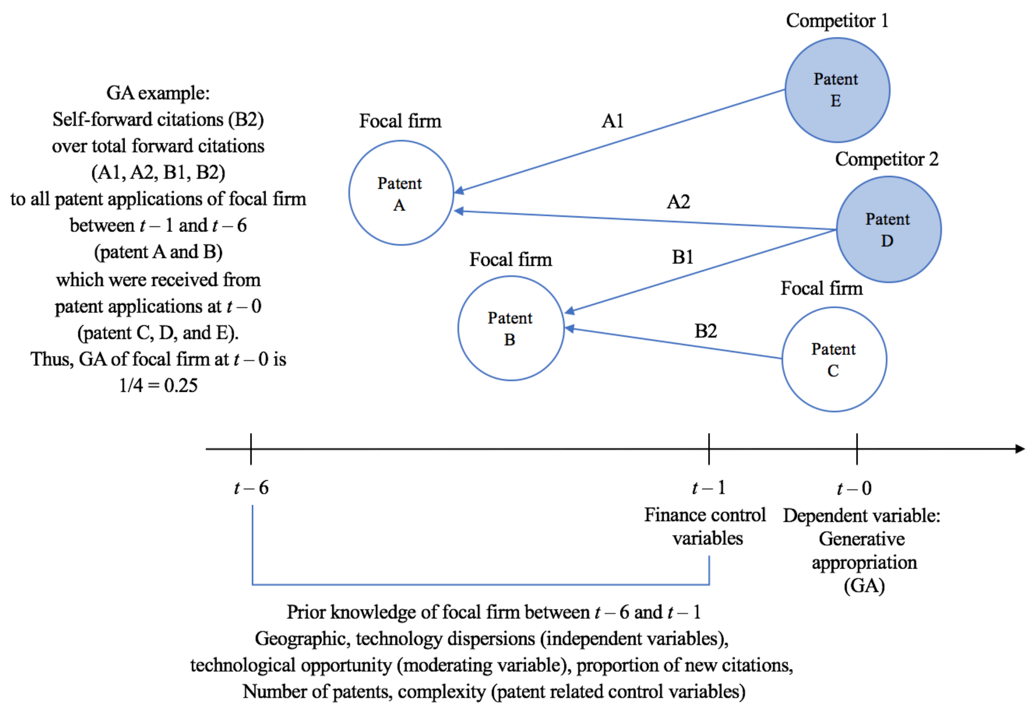

Figure 4.2. Generative Appropriation (GA) Variable Operationalization

Table 4.1. Pairwise Correlation and Descriptive Statistics

Logit-transformed values reported in parentheses. [a] Variables winsorized at 1% and 99% in each year to eliminate outliers; R&D intensity winsorized at 1% and 97%; N = 17,866; All correlations with an absolute value equal to or greater than 0.02 are statistically significant at $P < 0.05$.

Variables	Mean	Std. Dev.	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Generative appropriation (GA)	0.10 (-5.47)	0.17 (3.99)	0.00 (-9.21)	1.00 (9.21)													
2. Leverage [a]	0.14	0.19	0.00	1.35	0.00												
3. Firm performance [a]	0.03	0.52	-5.72	0.94	0.03	0.00											
4. Firm size	5.44	2.33	0.00	12.58	0.06	0.16	0.04										
5. Diversification	0.21	0.39	0.00	2.06	0.01	0.14	-0.02	0.49									
6. Patent stock	3.09	1.82	0.00	9.45	0.17	0.07	0.02	0.71	0.32								
7. R&D intensity [a]	1.14	5.62	0.00	13.46	0.03	-0.04	0.02	-0.17	-0.10	-0.08							
8. Search scope	0.82	0.17	0.19	1.00	-0.13	0.01	0.03	-0.13	0.01	-0.40	-0.05						
9. Technology complementarity	0.11	0.05	0.00	0.41	-0.02	-0.05	-0.01	-0.07	-0.08	-0.01	0.10	-0.10					
10. Technology complexity	2.20	0.94	0.18	12.94	0.08	0.10	0.00	0.08	0.09	0.03	0.04	-0.03	0.12				
11. Technology opportunity	1.21	0.92	0.03	5.62	-0.04	-0.07	-0.07	-0.12	-0.20	0.01	0.29	-0.21	0.34	0.08			
12. Technology dispersion	0.63	0.28	0.00	0.99	0.07	0.10	0.01	0.54	0.32	0.64	-0.10	-0.11	-0.06	0.11	-0.18		
13. Geographic dispersion	0.40	0.28	0.00	0.93	0.01	0.17	0.00	0.42	0.29	0.40	-0.02	-0.13	0.00	0.07	0.01	0.42	
14. GA Presample	0.13	0.15	0.00	1.00	0.33	0.01	0.03	0.08	0.01	0.31	0.08	-0.41	0.02	0.09	0.06	0.10	0.07

Table 4.2. Fixed Effects and Random Effects Regression Analyses

Robust standard errors, clustered by firms, in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Generative Appropriation (GA)						
Variables	FE	FE	FE	FE	FE	RE	RE
Leverage	-0.220	-0.182	-0.169	-0.148	-0.124	-0.121	-0.089
	(0.229)	(0.229)	(0.230)	(0.231)	(0.231)	(0.174)	(0.174)
Firm performance	0.098†	0.091	0.094†	0.087	0.091	0.181**	0.179**
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)
Firm size	0.485***	0.516***	0.512***	0.523***	0.521***	0.388***	0.389***
	(0.059)	(0.058)	(0.058)	(0.058)	(0.058)	(0.022)	(0.022)
Diversification	0.038	0.058	0.052	0.052	0.042	-0.148	-0.157
	(0.175)	(0.174)	(0.173)	(0.172)	(0.170)	(0.112)	(0.111)
Patent stock	0.709***	0.752***	0.749***	0.756***	0.753***	1.012***	1.012***
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.036)	(0.036)
R&D intensity	0.010	0.012	0.009	0.013	0.010	0.046*	0.047*
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.021)	(0.021)
Search scope	3.425***	3.717***	3.701***	3.695***	3.673***	1.164***	1.141***
	(0.327)	(0.331)	(0.331)	(0.330)	(0.330)	(0.242)	(0.241)
Technology complementarity	-0.750	-0.793	-0.659	-0.804	-0.648	-0.254	-0.292
	(1.794)	(1.790)	(1.802)	(1.772)	(1.778)	(0.870)	(0.870)
Technology complexity	-0.072	0.011	0.004	0.018	0.011	0.046	0.039
	(0.158)	(0.159)	(0.160)	(0.158)	(0.159)	(0.107)	(0.107)
Technology complexity squared	0.006	-0.004	-0.002	-0.005	-0.004	-0.002	-0.001
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.017)	(0.017)
GA pre-sample (10 year average)						1.532***	1.537***
						(0.349)	(0.349)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	NO	NO
Industry fixed effects	NO	NO	NO	NO	NO	YES	YES

(Continued)

Technology opportunity (TO)	-0.086	-0.138	-0.042	0.133	0.304†	-0.091	0.192*
	(0.115)	(0.115)	(0.121)	(0.161)	(0.171)	(0.063)	(0.096)
Technology dispersion		-1.162***	-2.066***	-1.191***	-2.281***	-0.785***	-1.480***
		(0.289)	(0.423)	(0.289)	(0.429)	(0.188)	(0.283)
Geographic dispersion		0.738	0.711	2.644**	2.878**	0.411	1.902**
		(0.647)	(0.647)	(0.961)	(0.962)	(0.444)	(0.696)
Geographic dispersion squared		-1.828*	-1.784*	-3.703**	-3.829**	-1.489**	-2.828**
		(0.827)	(0.826)	(1.251)	(1.245)	(0.549)	(0.882)
Technology dispersion × TO			0.763**		0.915**		0.550**
			(0.282)		(0.292)		(0.181)
Geographic dispersion × TO				-1.780**	-2.047**		-1.281**
				(0.653)	(0.656)		(0.454)
Geographic dispersion squared × TO				1.780*	1.982*		1.183*
				(0.836)	(0.834)		(0.592)
Constant	-9.817***	-10.247***	-10.270***	-10.570***	-10.662***	-8.940***	-9.230***
	(0.542)	(0.555)	(0.554)	(0.559)	(0.561)	(0.898)	(0.905)
Observations	17,866	17,866	17,866	17,866	17,866	17,866	17,866
Number of firms	2,615	2,615	2,615	2,615	2,615	2,615	2,615
R-squared	0.176	0.178	0.179	0.179	0.180	0.334	0.335

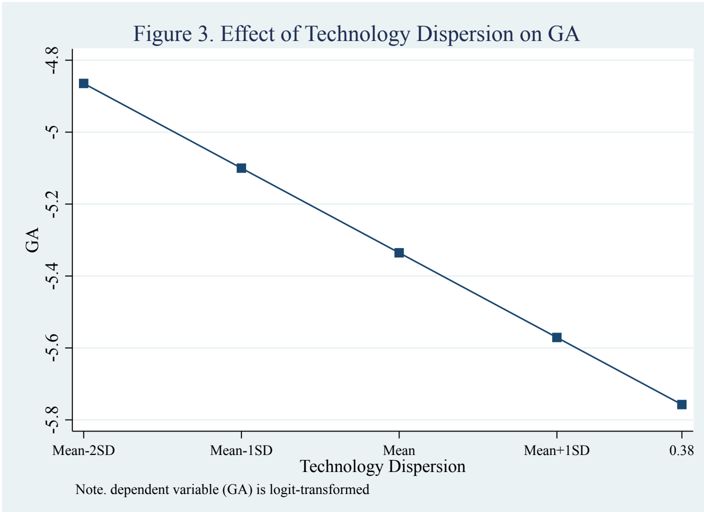

Figure 4.3. Effect of Technology Dispersion on GA

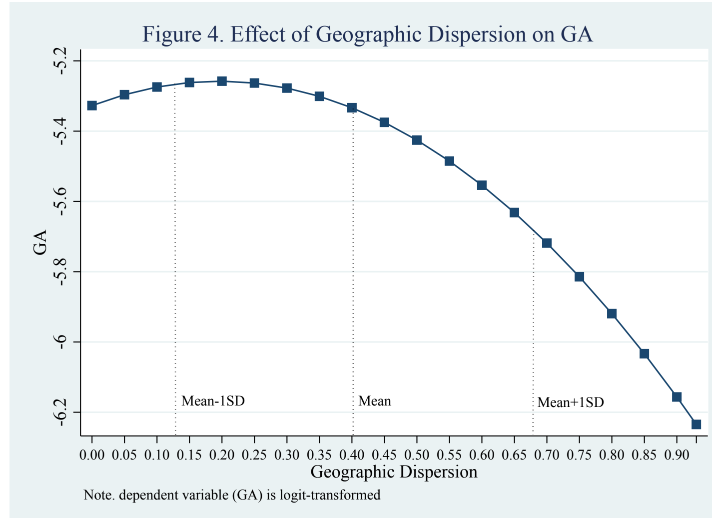

Figure 4.4. Effect of Geographic Dispersion on GA

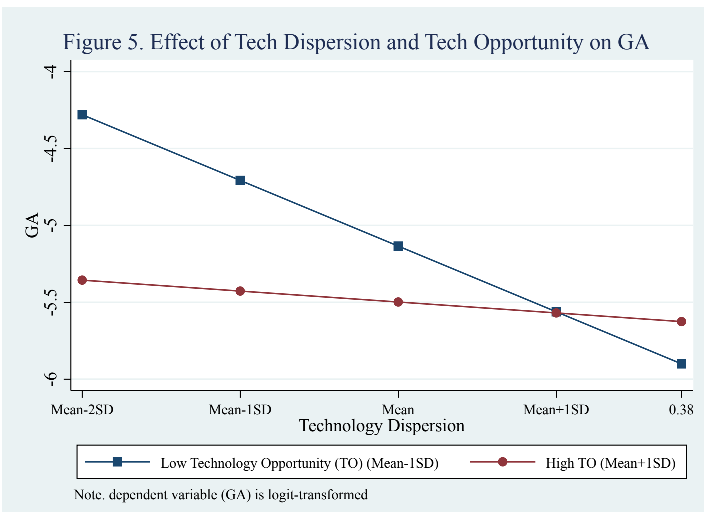

Figure 4.5. Effect of Technology Dispersion and Technology Opportunity on GA

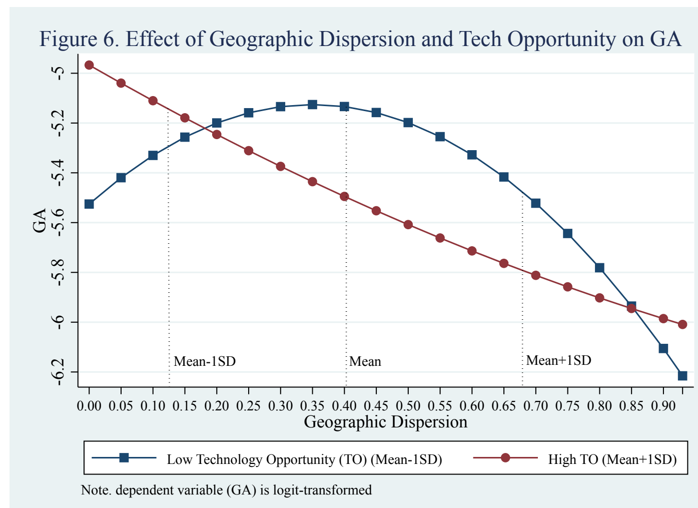

Figure 4.6. Effect of Geographic Dispersion and Technology Opportunity on GA

Table 4.3. Supplementary analyses

Robust standard errors, clustered by firms, in parentheses; *** $p<0.001$, ** $p<0.01$, * $p<0.05$, † $p<0.1$; The number of observations in both Model 1 and Model 2 are smaller than main analyses because of missing lagged dependent variable

Variables	Model 1 Ln(1+Other cites)	Model 2 Ln(1+Self cites)
Ln(1+Self cites) t-1	0.016*	0.389***
	(0.006)	(0.016)
Ln(1+Other cites) t-1	0.267***	-0.033**
	(0.010)	(0.012)
Ln(1+Self cites) t-0	0.032***	
	(0.006)	
Ln(1+Other cites) t-0		0.083***
		(0.015)
Leverage	-0.047	-0.007
	(0.044)	(0.060)
Firm performance	0.002	0.028*
	(0.010)	(0.014)
Firm size	0.030*	0.081***
	(0.012)	(0.015)
Diversification	-0.032	-0.049
	(0.027)	(0.044)
Patent stock	0.645***	0.204***
	(0.017)	(0.024)
R&D intensity	-0.001	-0.000
	(0.001)	(0.002)
Search scope	-0.164*	1.125***
	(0.064)	(0.081)
Technology complementarity	1.338***	0.702+
	(0.339)	(0.394)
Technology complexity	0.013	0.112***
	(0.032)	(0.033)
Technology complexity ^{2}	0.001	-0.013**
	(0.004)	(0.004)
Technology opportunity (TO)	-0.144***	0.111**
	(0.032)	(0.038)
Technology dispersion	-0.365***	-0.764***
	(0.087)	(0.095)
Geographic dispersion	-0.181	0.671**
	(0.180)	(0.217)
Geographic dispersion ^{2}	0.230	-0.663*
	(0.227)	(0.301)
Technology dispersion × TO	-0.039	0.356***
	(0.062)	(0.065)
Geographic dispersion × TO	0.030	-0.578***
	(0.133)	(0.155)
Geographic dispersion ^{2} × TO	-0.006	0.383+
	(0.160)	(0.207)
Constant	0.052	-1.644***
	(0.116)	(0.152)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	16,401	16,401
R-squared	0.650	0.407
Number of firms	2,438	2,438

5. GENERAL CONCLUSION

This dissertation has examined how firms create and capture value from their innovative activities. Given the importance of innovation for firm survival and growth, this dissertation may contribute to the innovation literature. This dissertation suggests that a common external threat in an industry affects how industry firms create value from innovative activities. This study also suggests that firm's appropriation strategy and knowledge dispersion affects how much value firms can capture from their innovative activities in terms of financial returns and share of derivative innovations spawned by existing innovations, respectively. Specifically, the findings of the second chapter suggest that, in the face of the external threat caused by bankruptcy, firms become conservative; as a result, they reduce innovative activities and the way they conduct innovative activities become conservative. The findings also suggest that the threat-rigidity effect from bankruptcy event is stronger for firms with higher own bankruptcy risk. The findings of third chapter suggests that trade secrecy has a positive effect on firm financial returns to R&D activities, but this effect is contingent upon concurrent use of other appropriation mechanisms and industrial conditions. The findings of the fourth chapter suggest that knowledge dispersion has significant effect on how much value firms capture from future innovation spawned by existing innovations and this effect is also contingent upon environmental condition – external technology opportunities.

Thus, all of the three studies in this dissertation suggest that environmental conditions strongly affect how much value firms create and capture from innovation activities. That is, the efficiency of value capture and value creation from innovative activities may depend on not only firm capabilities but also environmental conditions. Thus, when managers devise innovation strategy, they may carefully think about how its internal actions can improve its value creation and value capture from innovation activities as well as about how external environment can affect them.

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