THE GENERATION AND FLOW OF KNOWLEDGE IN TECHNOLOGY DEVELOPMENT

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Hyun Ju Jung

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THE GENERATION AND FLOW OF KNOWLEDGE IN TECHNOLOGY DEVELOPMENT

Approved by:

Dr. Jeongsik Lee, Chair
College of Business
Georgia Institute of Technology

Dr. John P. Walsh
School of Public Policy
Georgia Institute of Technology

Dr. Chris Forman
College of Business
Georgia Institute of Technology

Dr. Marco Ceccagnoli
College of Business
Georgia Institute of Technology

Dr. Alex Oettl
College of Business
Georgia Institute of Technology

Date Approved: August 26, 2013

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

Scholars in strategy, economics, and sociology of science and technology have studied technology development as a source of firms' economic gains as well as institutional changes. Drawing on the extant research of technology and innovation strategy, I investigate the problem of knowledge generation and flows in technology development. Specifically, I explore how firms generate novel technology and develop technological breakthroughs; how knowledge flows between firms affect interfirm cooperation in a knowledge network; and how science and technology programs impact the institutions of knowledge production.

In Essay 1 (Chapter 2), I examine the antecedents of knowledge recombination and technological breakthroughs. Conceptualizing a firm's exploration as a combinatory search of prior new-recombination (an original technology component), I investigate the impacts of prior new-recombination and search boundary (local vs. boundary-spanning) on the characteristics of focal invention. In particular, I theorize and juxtapose the contrasting effects of the boundary of technological search of prior new-recombination on the propensities that the focal invention generates new recombination and becomes a technological breakthrough. Specifically, I hypothesize that, when the technological search involves new recombination in prior inventions, 1) the likelihood of generating new recombination in the focal invention is greatest for a boundary spanning search, smallest for a local search, and intermediate for a hybrid search (which involves both types of search); but 2) the likelihood for the focal invention to become a technological breakthrough is greatest for a local search, smallest for a boundary spanning search, and

intermediate for a hybrid search. I find supporting evidence from the analysis of U.S. nanotechnology patents granted between 1980 and 2006.

The purpose of Essay 2 (Chapter 3) is to determine the effect of knowledge flows on the formation of interfirm cooperation. By distinguishing codified knowledge flows from tacit knowledge flows, this paper demonstrates that antecedents of interfirm cooperation lie in codified knowledge flows that precede interfirm cooperation. Two properties of asymmetry in directional codified knowledge flows, intensity and uncertainty, underpin this paper's arguments and empirical tests. The main finding in this study is that intense codified knowledge flows weaken the formation of interfirm cooperation. By mapping dyadic firms to a center and a periphery firm within a knowledge network, I theorize that the uncertainty of directional codified knowledge flows induces the center and the periphery firms to pursue interfirm cooperation differently. The results show that while uncertainty caused by distant technology components in knowledge flows hinders a center firm from pursuing interfirm cooperation, uncertainty stimulates a periphery firm to pursue interfirm cooperation. A statistical analysis performed on a sample of enterprise software firms between 1992 and 2009 supports the hypotheses of this paper.

In Essay 3 (Chapter 4), I examine how the National Nanotechnology Initiative (NNI), a most recent U.S. government's science and technology (S&T) program launched in 2000, impacts the nature of university research in nanotechnology. I characterize the NNI as a policy intervention that targets the commercialization of technology and a focused research direction to promote national economic growth. As such, I expect that the NNI has brought about unintended consequences in terms of the direction of university-industry knowledge flows and the characteristics of university research output in nanotechnology. Using the difference-in-differences analysis of the U.S. nanotechnology patents filed between 1996 and 2007, I find that, for the U.S. universities, the NNI has increased knowledge inflows from the industry, diminished the branching-out to novel technologies, reduced the research scope, and decreased the likelihood of technological breakthroughs, as compared to other U.S. and non-U.S. research institutions. The findings suggest that, at least in the case of the NNI, targeted S&T programs of the government may increase the efficiency of university research, but potentially do so at a considerable price.

CHAPTER 1

OVERALL RESEARCH GOAL AND IMPLICATION

Scholars in strategy, economics, and sociology of science and technology have studied technology development as a source of firms' economic gains as well as institutional changes. Drawing on the extant research of technology and innovation strategy, I investigate the problem of knowledge generation and flows in technology development in this dissertation.

Traditionally, scholars have focused on the relationship between technology development and socioeconomic evolution. One view contends that technology development determines social and economic activity (Marx, 1935; Shumpeter, 1975). Another view argues that in the social economic systems, technological progress is an endogenous variable (Shoomookler, 1966; Nelson and Winter, 1982). While both views seem to be extreme, the literature agrees on one point: technology development has played a central role in shaping long term social structure and economic growth by interacting with social and economic institutions (Sahal, 1985).

A strong body of literature has studied the process of technology development. Since Kuhn (1996) opened up the revolutionary view to examine the process of science research, scholars have adopted the implication of science research to the field of technology development (Nelson and Winter, 1977). They showed that science research and technology development involves a process of puzzle-solving through which scientists and engineers recombine existing knowledge across time and space (Schumpeter, 1939; Nelson and Winter, 1982). The outcome of this recombination, the generated knowledge, usually flows from region to region, field to field, institution to institution, and individual to individual. As Arrow (1962) discussed, knowledge flows induce the tension between the benefit of knowledge diffusion and appropriation for the outcomes of technology development. When science and technology policies emphasize the appropriation of technology development, institutions of knowledge production will be affected (Dasgupta and David, 1994; Nelson, 2004).

Building on this literature, my dissertation attempts to expand our understanding of the theoretical and empirical issues on technology development. As shown in Figure 1.1, the main constructs of this dissertation are three: knowledge generation, knowledge flows, and institutional changes. As a source of knowledge generation, I examine knowledge recombination, and as a consequence of knowledge generation, I focus on technological breakthroughs. I begin with a widely consented proposition that knowledge generation is the process of recombining existing knowledge components (Schumpeter, 1939; Nelson and Winter, 1982; Henderson and Clark, 1990; Rosenberg, 1996; Weitzman, 1998; Galunic and Rodan, 1998; Fleming, 2001). Following the evolutionary theory, the invention that serves as an input for future inventions will be substantive as a breakthrough in technology development (Trajtenberg, 1990; Ahuja and Lampert, 2001; Zucker, Darby, and Armstrong, 2002; Singh and Fleming, 2010). To recombine existing knowledge, organizations may draw not only on their own knowledge but also on others' knowledge. Thus, knowledge flows among different organizations (Nelson and Winter, 1982). For instance, firms quest for knowledge through interfirm cooperation (Mowery, Oxley, and Silverman, 1996; Uzzi, 1997; Kogut, 1988; Gulati, 1998). Given that interfirm cooperation accompanies expropriation risks (Teece, 1986; Williamson, 1991), I study the effect of pre-exiting knowledge flows on the formation of institutional cooperation between firms. And more broadly, substantive sources of knowledge generation and flows—universities—may be affected by institutional changes such as national science and technology (S&T) policy initiatives (Dasgupta and David, 1994). Thus, I examine commercialization-oriented S&T program as an institutional change that affect the phenomena of knowledge generation and knowledge flows. This dissertation consists of three essays, which explore unanswered questions regarding these constructs.

In the first essay (Chapter 2), I study the antecedents of knowledge new-recombination and technological breakthroughs. By tracing and examining new recombination in prior and focal invention, I extend the idea put forth by Romer (1994), Weitzman (1998), and Fleming (2001) that new recombination can be a source for technological breakthroughs. Also, I examine the search for new recombination in the context of local searches as well as boundary spanning searches. The search for new recombination may markedly vary the well-known impacts of local and boundary spanning searches on technology development (Rosenkopf and Nerkar, 2001). I suggest that local searches for new recombination contribute to bring about technological breakthroughs while boundary spanning searches for new recombination contribute to generate novel technology.

In the second essay (Chapter 3), I examine the effect of knowledge flows on interfirm cooperation. A strong body of literature argues that interfirm cooperation stimulates knowledge flows. In general the literature that studies the effect of interfirm cooperation on knowledge flows assumes that interfirm cooperation is exogenous to knowledge flows between firms. However, the assumption is debatable because knowledge may flow before the formation of interfirm cooperation. I study this issue with a novel approach. I distinguish codified and tacit knowledge flows because the conflation of codified knowledge and tacit knowledge causes part of the difficulty in explaining the triggering effect of knowledge flows on interfirm cooperation. Because tacit knowledge usually flows in the setting of a direct relationship, such as interfirm cooperation, tacit knowledge may not flow before interfirm cooperation. In this essay, I suggest that codified knowledge flows decrease the formation of interfirm cooperation because codified knowledge flows may substitute the need for tacit knowledge and, thus, reduce the formation of interfirm cooperation.

The third essay (Chapter 4) studies the impact of commercialization-oriented science and technology programs on university research. I show how the institutional changes, such as the conception of government science and technology initiatives, affect the institution of knowledge generation, i.e., universities. It has been generally understood that universities specialize in basic research (Nelson, 1959; Dasgupta and David, 1994), advance technology developments by often bringing about serendipitous exploration and technological breakthroughs (Mansfield, 1991;Nelson, 2004), and operate on a functional norm that research findings should be universally available to the research community (Merton, 1973). I suggest that the government-mandated missions such as ensuring national economic leadership and industrial competitiveness may significantly affect the institutions of knowledge production and, hence, alter the landscape and flows of knowledge.

I aim to contribute to technology and innovation strategy literature by examining the development of novel technologies and technological breakthroughs as well as knowledge flows. The findings imply that the path for technology development may be randomly dispersed branching-outs from prior nodes of technology to the next nodes of technology. These branching-outs to subsequent technologies occur in a process through which the components of accumulated prior knowledge are recombined. Therefore, accessing prior knowledge is essential for developing a novel technology or a technological breakthrough. Hence, science and technology programs should play important roles in facilitating knowledge accessibility and thus shaping knowledge flows. The knowledge flows that transport technology components from one node of technology to another across time and space may be not only the result but also the cause of institutional changes. Finally, the generation of novel technology plays a significant role in technology development not only because novel technologies indicate technological breakthroughs but also because novel technologies induce subsequent inventions that draw on and experiment them to yield superior technological outcomes.

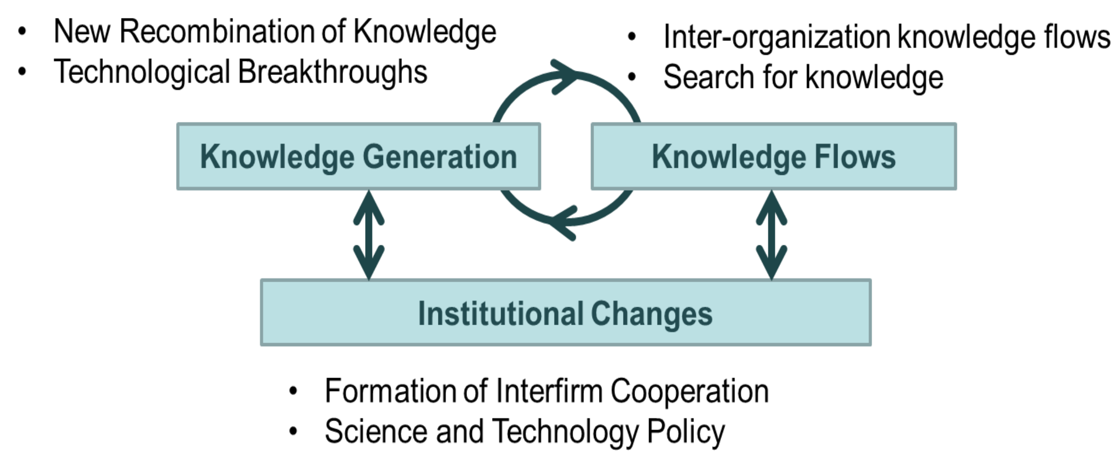

Figure 1.1 Research Framework

References

Ahuja, G., & Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22: 521–543.

Arrow, K. 1962. Economic welfare and the allocation of resources for invention. The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press, Princeton, NJ.

Dasgupta, P. & David, P. 1994. Towards a new economics of science. Research Policy 23: 487–522.

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science 47: 117–132

Galunic C, Rodan S. 1998. Resource recombinations in the firm: knowledge structures and the potential for Schumpeterian innovation. Strategic Management Journal 19(12): 1193–1201.

Gulati R. 1998. Alliances and networks. Strategic Management Journal, Special Issue, 19: 293–317.

Henderson, R.M. and Clark, K. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms, Administrative Science Quarterly 35: 9-30.

Nelson, R. 2004. The market economy, and the scientific commons. Research Policy 33(3): 455-471.

Kogut, B. 1988. Joint ventures: Theoretical and emperical perspectives. Strategic Management Journal, 9(4): 319–332.

Kuhn, T. S.1996. The Structure of Scientific Revolutions 3rd ed., Chicago: The Chicago University Press.

Mansfield, E. 1991. Academic research and industrial innovation. Research Policy 20:1-12

Marx, K. 1935. The Poverty of Philosophy. Cooperative Publishing Society. Moscow

Merton, R. 1973. The sociology of science: Theoretical and empirical investigations. University of Chicago Press, Chicago, IL.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, Winter Special Issue, 17: 77–92.

Nelson, R. 1959. The simple economics of basic scientific research. Journal of Political Economy 67(3): 297-306.

Nelson, R.R., Winter, S.G., 1977. In search of useful theory of innovation. Research Policy 6 (1), 36–76.

Nelson, R., Winter, S. 1982. An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Romer, PM. 1994. Economic Growth and Investment in Children. Daedalus CXXIII: 141-154.

Rosenberg, N. 1996. Uncertainty and technological change. R. Landau, R. Taylor, G. Wright, eds. The Mosaic of Economic Growth. Stanford University Press, Stanford, CA.

Rosenkopf, L., Nerkar, A. 2001. Beyond local search: Boundary spanning, exploration, and impact in the optical disc industry. Strategic Management Journal 22(3): 287–306.

Sahal, D. 1985. Technological guideposts and innovation avenues. Research Policy 14 61–82.

Schmookler, J. 1966. Invention and Economic Growth. Harvard University Press, Cambridge.

Schumpeter, J. 1939. Business Cycles. McGraw-Hill Book Company, Inc.: New York.

Schumpeter, J. 1975. Capitalism, Socialism, and Democracy. Harper and Row Publishers: New York.

Singh, J., Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? Management Science 56(1): 41-56.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, cooperation, licensing and public policy. Research Policy, 15: 285–305.

Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovations. Rand Journal of Economics. 21 172–187.

Uzzi, B.1997. Social structure and competition in interfirm networks: The paradox of embeddedness. Administrative Science Quarterly, 42: 36–67.

Weitzman, M.L. 1998. Recombinant growth. Quarterly Journal of Economics 113: 331–360.

Williamson, O. E. 1991. Comparative economic organization: the analysis of discrete structural alternatives. Administrative Science Quarterly, 36: 269-296.

Zucker, L., Darby, M., Furner, J., Liu, R., & Ma, H. 2007. Minerva unbound: Knowledge stocks, knowledge flows and new knowledge production. Research Policy 36(6): 850-863.

CHAPTER 2

SEARCH BOUNDARY, KNOWLEDGE RECOMBINATION, AND TECHNOLOGICAL BREAKTHROUGHS

1 Introduction

A significant body of literature argues that the recombination of prior knowledge components is the source of novelty (Schumpeter, 1939; Nelson and Winter, 1982; Weitzman, 1998). Researchers have also emphasized the importance of new recombination of prior knowledge, experiences, routines, or technologies as a potential generator of technological breakthroughs (Nelson and Winter, 1982; Kogut and Zander, 1992; Romer, 1994; Weitzman, 1998; Fleming, 2001). Henderson and Clark (1990) demonstrate that reconfiguring or rearranging existing technological components in a novel way can create destructive technological changes. For instance, the ceramic, a mixture of four elements (i.e., copper, barium, oxygen, and yttrium), that turned out to be a superconductor when placed under different conditions of temperature and pressure (Romer, 1994). Another example is an "electronic candle" Edison developed by testing over 6,000 new combinations with filament materials that came from all over the world (Weitzman, 1998). Despite the existing literature's emphasis on the importance of new recombination and salient anecdotal examples, we have limited understanding of the antecedents of new recombination and the mechanisms through which these antecedents lead to technological breakthroughs.

The creation of new recombination has been interpreted as firms' exploration that increases the variance of technological outcomes and, hence, the uncertainty surrounding the success or failure of the technologies (March, 1991; Fleming, 2001). Exploration is associated with such terms as search, variation, experiment, risk-taking and innovation (March, 1991), and is likely to produce technological breakthroughs by increasing performance outliers including both cases of success and failure (March, 1991; Fleming, 2001). Exploration has thus been firmly understood as an important mechanism that leads to technological breakthroughs (Cohen and Levinthal, 1990; Henderson and Clark, 1990; Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001).

The prominent literature highlights the role of firms' exploration such as boundary spanning search (i.e., search beyond localness) in developing technological breakthroughs (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Henderson and Clark, 1990; Kogut and Zander, 1992; Ahuja and Lampert, 2001; Fleming, 2001; Rosenkopf and Nerkar, 2001). These studies richly document that firms explore by searching unfamiliar knowledge components and recombining the components in a novel way. However, it appears to us that two different forms of exploration—searching for newly recombined components and generating new recombination—have been conflated, both conceptually and empirically.

We argue that *what* components firms search for (for-search exploration) should be distinguished from *how* firms recombine them (for-generate exploration). For instance, from the above example, searching for a ceramic (i.e., new recombination of four elements) and generating new recombination of a ceramic, heat and pressure may each represent a different style of explorations in developing superconductor technologies.[1] However, very little is known about the relationship between firms' exploration in *searching* for new recombination in prior knowledge and their exploration in *generating* new recombination in focal inventions. We believe that, for at least three reasons, it is important to better understand this relationship. First, it is not at all clear whether for-search exploration necessarily leads to for-generate exploration. Second, searching for new recombination in prior technologies may affect the development of technological breakthroughs differently from the way in which generating new recombination in focal invention does. Third, the search of new recombination may vary markedly between the boundaries of search, i.e., local vs. boundary spanning, in terms of their influence on technology developments. We therefore address this issue by examining the effect of new recombination in prior inventions (hereafter, prior new-recombination) on the generation of new recombination in focal inventions (hereafter, focal new-recombination) and on the development of technological breakthroughs, with respect to the boundary of the search (i.e., *where* firms look for the prior new-recombination).

Our intended contribution to the literature is twofold. First, we add to the literature of recombinant knowledge. Interestingly, the existing knowledge component that a focal invention draws from prior inventions can be either "original" (in the sense that it represents the first-ever recombination of preceding knowledge components) or "ordinary" (i.e., contains no such new recombination). This suggests an opportunity to

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[1] March (1991) captures exploration using terms such as search, variation, experimentation, discovery, and innovation. Building on these terms, we map "for-search" exploration to search, variation, or experimentation, and "for-generate" exploration to discovery or innovation.

extend the idea put forth by scholars such as Romer (1994), Weitzman (1998), and Fleming (2001) that new recombination can be a source of technological breakthroughs. The literature, in general, identifies a focal new-recombination and then examines how the focal new-recombination is related to the probability of technological breakthroughs. Yet, prior new-recombination may exert distinct influences, separately from those of focal new-recombination, on the focal invention's characteristics. That is because, while generating new recombination may itself create technological uncertainty (Fleming, 2001), incorporating prior new-recombination may address, at least partially, the technological uncertainty that the prior new-recombination had triggered.

Second, we contribute to the literature of exploration by examining the exploration for prior new-recombination with respect to the boundary of search. Extending the literature on path dependency and technology-development trajectory (Nelson and Winter, 1977; 1982; Dosi, 1982; Cohen and Levinthal, 1990; Cohen, 2010), many scholars have demonstrated that firms exhibiting superior outcomes tend to explore beyond local boundary, while striking a balance between local and boundary spanning searches (Rosenkoph and Nerkar, 2001; Nerkar, 2003; Rothaermel and Alexandre, 2009; Kotha, Zheng, and George, 2011). In doing so, scholars seem to have considered a local search as exploitation (Fleming, 2001) or at least a lower degree of exploration (Rosenkopf and Nerkar, 2001) compared to a boundary spanning search.[2] However, an

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[2] For instance, Fleming (2001) states that "…Localness corresponds to inventors' familiarity with their recombinant search space. Local search or exploitation (March 1991) occurs when an inventor recombines from a familiar set of technology components or refines a previously used combination…" (p. 119). Rosenkopf and Nerkar (2001) also describe that a local search enables firms to have "first-order competence" and a boundary spanning search to have "second-order competence." They emphasize that

extensive form of exploration can be found even within a local search. For instance, while exploring to attain significant research outcomes, firms may encounter first-ever introduced new recombination that represents an original technology component within their local technological domain. Since original technologies are often in very primitive forms (Rosenberg, 1996), firms should experiment with these undefined technologies to turn them into useful inputs for technological developments.

To decouple from the potential conflation between the level of exploration and the boundary of technological search, we must keep one of the dimensions constant and examine the other. We control for the level of exploration by focusing on the search of prior new-recombination. By holding constant the explorative characteristic of local and boundary spanning searches at the search of the prior new-recombination, we can provide a condition for a controlled identification of the *net* impacts of local and boundary spanning searches, independent of the effects from different degrees of exploration in technological searches in *any* boundary. This approach thus advances the current literature in an important way. For instance, Rosenkopf and Nerkar (2001) show in their prominent study of the optical disc technology that, by searching for prior technological components—whether or not the component is an original technology—beyond the local technology boundary, firms produce technological breakthroughs. We note that the demonstrated difference in technological performance between local and boundary spanning searches is possibly driven by the difference between a relatively *exploitative*

"… our focus is on what we call 'second-order competence': the ability of a firm to create new knowledge through recombination of knowledge across boundaries…"

local search and an *explorative* boundary spanning search, rather than by the difference in search boundaries per se. By exploiting the phenomena that firms explore new recombination both outside and inside of their technological domains, we compare the exploration in a local search with that in a boundary spanning search.

We argue that, with a local search, prior new-recombination is less likely to be rearranged or reconfigured in a new context. That is because, within a local domain, the prior new-recombination binds the focal invention to its own technology development trajectory, thereby limiting the focal invention from creating new recombination. On the other hand, standard procedures and shared assumptions along the technology development trajectory facilitate the focal invention's improvement of the unresolved and untested problems surrounding the prior new-recombination. As a result, the focal invention reduces the technological uncertainty associated with the prior new-recombination and thus is likely to have a high impact on subsequent inventions. Conversely, with a boundary spanning search for prior new-recombination, a focal invention is more prone to generating new recombination by transporting the prior new-recombination from the outside to the inside of a technology boundary. However, the standard procedure or research method along the local technology development trajectory may not reduce the technological uncertainty of the prior new-recombination brought in from the outside of a technology boundary as effectively as in that searched inside. Consequently, the impact of the focal invention with a boundary spanning search for prior new-recombination on subsequent inventions will be lower. A "hybrid" search that includes both local and boundary spanning searches is then likely to exhibit an intermediate effect on the characteristics of the focal invention.

Building on the argument above, we hypothesize as follows on the effect of different types of search on focal inventions: when the technological search involves new recombination in prior inventions, 1) the likelihood of generating new recombination in the focal invention is greatest for a boundary spanning search, smallest for a local search, and intermediate for a hybrid search; but 2) the likelihood for the focal invention to becomes a technological breakthrough is greatest for a local search, smallest for a boundary spanning search, and intermediate for a hybrid search.

We test these hypotheses on the data of inventions in the field of the U.S. nanotechnology. Nanotechnology presents an ideal setting for this study. The paper's focus on firm-generated new recombination and technological breakthroughs requires that firms generate significant knowledge in the technology. In nanotechnology, firms have indeed contributed actively and importantly to the technological advancement. For instance, the invention of the Scanning Tunneling Microscopy (STM) came from IBM in early 1980s. NEC, a Japanese company, discovered carbon nanotubes in 1990s. Also, because nanotechnology is not yet in a commercially mature stage (NSTC, 2011), a plenty of room for technological advancements exist so that we continue to observe abundant firm activities regarding the recombination of existing technologies and the development of technological breakthroughs. In particular, given the multidisciplinary nature of research, significant search activities both inside and outside the technological boundary may be crucial for achieving technological developments. Moreover, our main constructs (i.e., new recombination and technological breakthroughs) can be significant factors in determining the technology and innovation strategy of firms, regardless of their size, that intend to obtain Schumpeterian rents (Schumpeter, 1975) in this technology space.

Our analysis of U.S. firm nanotechnology patents granted between 1980 and 2006 corroborates the hypotheses. The empirical findings highlight that : 1) with a local search, incorporating prior new-recombination into the focal invention decreases the propensity of generating new-recombination in the focal invention but increases the likelihood of the focal invention to become a technological breakthrough; and 2) with a boundary spanning search, relative to a local search, incorporating a prior new-recombination into the focal invention improves the chances of focal new-recombination but leads to a lower likelihood of a technological breakthrough.

2 Theory and Hypothesis

2.1 New Recombination in Prior and Focal Inventions

To develop the arguments on the links between the search of prior new-recombination, the generation of focal new-recombination and the development of technological breakthroughs, we first elaborate the concept of new recombination. Knowledge creation is the process of recombining existing knowledge components (Schumpeter, 1939; Nelson and Winter, 1982; Henderson and Clark, 1990; Rosenberg, 1996; Weitzman, 1998; Galunic and Rodan, 1998; Fleming, 2001). Recombination begins with searches of knowledge components (Nelson and Winter, 1982; Rosenkopf and Neckar, 2001) and is processed through merges of diffused knowledge components (Jaffe, 1986; Cohen and Levinthal, 1990; Griliches, 1992). The literature defines recombinative components as: "conceptual or physical materials," such as routines or technologies (Nelson and Winter, 1982; Galunic and Rodan, 1998); "old knowledge," such as existing cultivated plant varieties (Weitzman, 1998); pre-existing "elements," such as materials in periodic tables, and "conditions," such as temperature and pressure (Romer, 1994); and "constituents of invention," such as Schumpeterian "factors" (Schumpeter, 1939; Fleming, 2001). In line with this literature, we define "components" to denote the existing technological knowledge. Knowledge components can be inputs for recombination in focal inventions as well as results of recombination in prior inventions. Through new recombination, knowledge components may expand in combinatoric manner (Romer 1994; Weitzman, 1998).

While there are theoretically an infinite number of potential combinations of knowledge components (Weitzman, 1998), only a part of them are realized in inventions. And some of these inventions incorporate original new recombination that did not exist before. Firm exploration may involve this new recombination in two ways. First, firms may generate new recombination in focal inventions (Weitzman, 1998; Fleming, 2001). Second, firms may search and use new recombination in prior inventions as components for their own recombination.

The inventions from the first type of exploration that generates focal new-recombination are disproportionally more likely to be either successful or poor outcomes (March, 1991; Fleming, 2001). This implies that newly generated recombination may introduce technological uncertainty in the sense that the impact of the new recombination cannot be fully appreciated ex-ante (Rosenberg, 1996; Fleming, 2001). Thus, focal new-recombination per se may not suggest a successful outcome, i.e., a technological breakthrough that firms should be eventually interested in. In contrast, we expect that the second type of exploration that searches for prior new-recombination may reduce technological uncertainty of the prior new-recombination. Technological uncertainty arises from unpredictability in future usages of a novel technology or future technological changes following the development of the technology (Rosenberg, 1976). Hence, incorporating prior new-recombination into a focal invention may lessen the technological uncertainty that the prior new-recombination has triggered. Consequently, the focal invention is likely to prove useful for subsequent technology developments and thus become highly successful.

2.2 Searches of Prior New-Recombination and Technological Breakthroughs

From the perspective of evolutionary theory, the invention that serves as an input for future inventions is essential for technology developments. Thus, an invention can be regarded as successful when other researchers recognize and build on that invention (Simonton, 1999; Fleming, Mingo, and Chen, 2007). Following prior studies (Trajtenberg, 1990; Ahuja and Lampert, 2001; Zucker, Darby, and Armstrong, 2002; Singh and Fleming, 2010), we define a technological breakthrough as an invention that has been exceptionally frequently used by subsequent inventions.[3]

Practically, a technological breakthrough can be determined by an invention-specific value regarding the degree of usefulness for future technology developments. Given that the value distribution of inventions is highly skewed (Griliches, 1990; Harhoff et al, 1999), we focus on the highly impactful portion of inventions. Technological

[3] This definition is distinguished from that of Tushman and Anderson (1986) in which a technological breakthrough means competence-destroying technological discontinuity. In our definition, a technological breakthrough includes both radical and incremental technology developments.

breakthroughs play critical roles in promoting entrepreneurial activities, increasing welfare, and creating Schumpeterian rents (Schumpeter, 1975; Trajtenberg, 1990; Harhoff et al, 1999). Further, firms may be particularly interested in developing technological breakthroughs because these breakthroughs have been sources of growth and new business developments (Burgelman, 1983; Ahuja and Lampert, 2001).

A significant body of literature establishes that technological breakthroughs are induced by firms' exploration to search for knowledge beyond their local domain. In general, scholars propose that, through a local search, firms can accumulate knowledge stocks and capabilities to continuously innovate (Cohen and Levinthal, 1989; Stuart and Podolny, 1996) but, through a boundary spanning search, firms can overcome path dependency and achieve technological breakthroughs (Ahuja and Lampart, 2001; Fleming, 2001; Rosenkopf and Nerkar, 2001).The literature seems to put more weights on boundary spanning searches than on local searches in identifying the indicator of technological breakthroughs.

What it remains unclear in this literature is *what* firms actually search for when exploring in prior technologies. The degree of exploration and the associated uncertainty are determined not only by the domain of search (e.g., local vs. cross-boundary) but also by the target of search (e.g., original vs. conventional). To unambiguously identify the link between search boundary and the characteristics of resulting inventions, one needs to adequately control for the source of variation arising from differences in search targets. To this end, we focus on searches of prior new-recombination that was first-ever introduced. It is generally considered that a local search is less explorative in nature (Rosenkopf and Nerkar, 2001; Fleming, 2001; Ahuja and Katila, 2004). However, given that this original new-recombination is in an underdeveloped and uncertain condition (Rosenberg, 1996) and thus invokes many unsolved problems (Simonton, 2004)[4], locally searching for the original technologies is likely to be no less explorative than searching for knowledge components across boundaries. If firms want to exploit relatively well-proven examples, they may simply search imitated, applied, or updated versions of the original technology. In contrast, searching for the original new-recombination, even within the boundary of a technology field, means that firms may aspire to explore uncertain aspects of the prior new-recombination.[5] The purpose of this exploration is to add significant technological advances such as new examples and solutions to the local field (Dosi, 1982), which is an unusual practice of firms in that firms have a tendency to exploit existing solutions (Ahuja and Lampert, 2001). Firms' attempts to find new solutions are risky and render no guarantee in outcomes (March, 1991; Ahuja and Lampert, 2001).

Figure 2.2 schematically summarizes these concepts in a two-by-two matrix. On the dimension of search boundary, two boundaries of search exist when a focal invention draws on prior inventions: a local boundary or a cross-boundary; and, on the dimension of search target, there are two kinds of components that a focal invention searches for: an ordinary component or new recombination (i.e., an original component). Hence, these

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[4] Simonton (2004) suggests that original discoveries are usually unreasonable and lack predetermined solutions and thus follow-up researches that address original problems are important in further developing the original discoveries. To comprehend original discoveries requires subsequent researches that process logical justification. With only these follow-up researches, the original discoveries can be accepted and established throughout the research community (pp.163-164).

[5] Interviews with researchers in nanotechnology confirmed this story. The interviewees mentioned that it is usually easier to follow examples that *interpret* or *apply* prior original technologies; however, significant outcomes usually result when they go back to and examine the very original technologies in the field.

together generate four types of searches: an *ordinary search* that incorporates no prior new-recombination, a *boundary spanning search* that incorporates prior new-recombination from outside the local domain, a *local search* that incorporates prior new-recombination from inside the local domain, and a *hybrid search* that incorporates prior new-recombination from both inside and outside of the local domain.

2.3 Search Boundaries and Focal New-recombination

Within a local technology field, technology developments may proceed along a "trajectory," as if the trajectory moves toward some physical limits (Nelson and Winter, 1977; Dosi, 1982; Cohen, 2010). Put differently, a technology trajectory has a certain inner logic of its own such as expectations for the direction of progress. This trajectory is thus related to firms' technological development efforts that tend to be concentrated on a limited number of distinct, identifiable problems such as technological bottlenecks and targets for improvement (Nelson and Winter, 1977; Rosenberg, 1996). When addressing prior new-recombination, a focal invention may be expected to solve these trajectory-specific problems by testing uncertain technologies around the prior new-recombination (cf. Kuhn, 1996).[6]

On the other hand, firms have a tendency toward local searches (March and Simon, 1958; Nelson and Winter, 1982; Cohen and Levinthal, 1990; Ahuja and Katila, 2004; Hansen and Lovas, 2004). A local search implies that firms search within the boundary of a specific technology field in which they have built a series of proximate

[6] This style of problem solving by firms along the technological trajectory is analogous to the puzzle-solving by scientists as Kuhn (1996) suggests (Dosi, 1982). According to Kuhn (1996), scientists are puzzle-solvers who dedicate their efforts to actualize promises of a specific scientific paradigm.

technological experiences (Nelson and Winter, 1982). A local search may result in a finding of prior new-recombination that was first-ever introduced. That prior new-recombination may, however, embody unresolved problems and untested technologies (Utterback, 1971; Abernathy and Utterback, 1975; Tushman and Anderson, 1986; Klepper, 1997), some of which the searching firms must address in their focal inventions.

Given that a technology trajectory is constrained in its own viewpoints toward problem solving, the searched prior new-recombination is less likely to be put in a new context other than the context of the local technology trajectory. Moreover, a focal invention may examine and adopt prior new-recombination by using standard procedures or methodologies that the technology trajectory embraces (Dosi, 1982; cf. Kuhn, 1996).[7] These standard procedures and methodologies may agree well, at least seemingly, with the prior new-recombination when it is searched locally along the same technology trajectory (Dosi, 1982; Levinthal and March, 1993). This apparent fit with standard procedures and methodologies, in addition to being on the same technology trajectory, may render the focal invention less apt to move the prior new-recombination to a different context outside the trajectory. For instance, when Graham Bell first invented the telephone technology in 1876, even the inventor himself failed to recognize it as a new technology but only considered it as “the improvement of telegraphy” (Rosenberg, 1996; Brock, 2009)[8]. This example shows how difficult it is ex-ante to depart from one context to another, such as from telegraph to telephone. As such, rearranging or reconfiguring the

[7] The standard procedures and methodologies may match to “rules,” “established viewpoint,” or “preconception” in Kuhn (1996, p.39).
[8] In fact, Bell filed the patent under the title “the improvement of telegraphy”. (Brock, 2009)

locally-searched prior new-recombination into a new context may occur much less frequently, or at least get delayed (cf. Kuhn, 1996) [9].

Relative to a local search, a boundary spanning search for prior new-recombination accompanies transporting of the searched prior new-recombination from the outside to the inside of a specific technology domain. Since the prior new-recombination that is found through a boundary spanning search should be rearranged and reconfigured in a new context, the focal invention is likely to embrace "architectural" changes (Henderson and Clark, 1990). By transporting the prior new-recombination into the local trajectory of technology development, the focal invention creates technological connections and integrations surrounding the prior new-recombination. These new connections and integrations may thus lead to another new recombination in the focal invention.

Further, by providing the opportunities of experimenting and transporting the prior new-recombination from the outside to the inside of the local field, a boundary spanning search may enable firms to incorporate an idiosyncratic knowledge structure (Simon, 1985) that is less bounded to standard procedures or assumptions within a specific technology trajectory. This varied knowledge structure is likely to create new ideas (Simon, 1985) that are relatively free from the problems that are identified as targets and hence are taken for granted in the technology trajectory. These new ideas may

[9] This argument is parallel to Kuhn's explanation about belated discoveries under normal science. Scientists stick to instrumental and theoretical expectations that standard procedures in normal science embrace. Thus, when new evidence emerges in a field, scientists cannot develop it directly to a new discovery. One such example is the identification of oxygen gas by Lavoisier in the eighteenth century. Even though it was before 1772 that evidence emerged on the existence of "good gas," it was not until after 1777 that the discovery of oxygen was officially recognized (Kuhn, 1996, pp. 59-60).

thus be less redundant with other ideas that have emerged along the technology trajectory (Podolny and Stuart, 1995). Consequently, focal inventions based on these new ideas may exhibit a greater likelihood of generating new recombination. As such, a boundary spanning search for prior new-recombination promotes the generation of focal new-recombination.

A hybrid search incorporates both a local search and a boundary spanning search. Given their contrasting effects on the generation of focal new-recombination, we expect that a hybrid search for prior new-recombination will exhibit an intermediate effect on the likelihood of focal new-recombination. This is because the positive effect of the boundary spanning search is likely to be offset, at least partially, by the countering effect of the local search. Therefore, new recombination in a focal invention is most likely to be attained by a boundary spanning search of prior new-recombination and is least likely to be attained by a local search, with a hybrid search exhibiting an intermediate effect. Formally:

Hypothesis 1: When the technological search involves new recombination in prior inventions, the likelihood of generating new recombination in the focal invention is greatest for a boundary spanning search, smallest for a local search, and intermediate for a hybrid search, relative to that for an ordinary search that involves no prior new-recombination.

2.4 Search Boundaries and Technological Breakthroughs

When prior new-recombination is locally searched, the experiments around the prior new-recombination may generate knowledge that provides a one-step-ahead understanding of the specific problems raised by the prior new-recombination. These experiments may involve a process of assessing and assimilating the prior new-recombination (Cohen and Levinthal, 1990), which would go through testing, modifying, or adopting uncertain technological aspects of the prior new-recombination. By this process, the focal invention can enclose some evaluative information about the locally-searched prior new-recombination (Fleming and Sorenson, 2004), which may consequently reduce the technological uncertainty that the prior new-recombination has created. In other words, the resolution of technological uncertainty of the prior new-combination is contingent on how much other inventions on the trajectory improve the original yet primitive component (Podolny and Stuart, 1995). The following illustrates this point. When Binnig and Rohrer from IBM invented the STM, a boundary spanning search for the "tunneling" phenomena contributed to the initial new recombination of the STM.[10] However, the actual success of the STM came from subsequent STM R&D efforts that drew on this original invention. That is, the IBM researchers generated the new recombination of the STM and then went back to this original component to develop a breakthrough technology for the STM in subsequent inventions.[11]

Recall that a technological development trajectory contains standard procedures and consented premises such as theoretical expectations and problem-solving heuristics

[10] "…So Binnig and Rohrer decided to build their own instrument – something new that would be capable of seeing and manipulating atoms at the nanoscale level. To do that, they began experimenting with tunneling, a quantum phenomenon in which atoms escape the surface of a solid to form a kind of cloud that hovers above the surface; when another surface approaches, its atomic cloud overlaps and an atomic exchange occurs…" (http://www-03.ibm.com/ibm/history/ibm100/us/en/icons/microscope/, accessed on April 13, 2013)

[11] These IBM researchers describe how they turned the 'unsuccessful' prior new-recombination into 'successful' technologies in subsequent developments. "…Previous developments were unsuccessful for various reasons. The present letter contains the first experimental results on surface topography obtained with this novel technique. They demonstrate unprecedent resolution of STM and should give a taste of its fascinating possibilities for surface characterization…" (Binnig et al., 1982)

(Dosi, 1982; cf. Kuhn, 1996). The locally-searched prior new-recombination is likely to nicely accommodate these shared theoretical and instrumental guidelines. With these guidelines, a focal invention may well advance the reduction of the technological uncertainty surrounding the target prior new-recombination. This is because, under the assumption of bounded rationality, the standard procedures and agreed-upon premises facilitate the interpretation and understanding of the uncertainty associated with the prior new-recombination, and hence, will be effective in resolving that uncertainty (Simon, 1996, p.42).

As a focal invention reduces the technological uncertainty of the locally-searched prior new-recombination, it clarifies technological opportunities to change and improve upon the prior new-recombination (Abernathy and Utterback, 1975; Rosenberg, 1996). The understanding and interpretation of the technological uncertainty may include some evaluative information, either positive or negative, about the prior new-recombination. For instance, the focal invention can greatly increase reliability on the prior new-recombination (Fleming and Sorenson, 2004), make complementary technologies ready (Adner and Kapoor, 2010), provide a better alternative such as a technology with lower adoption cost (Rosenberg, 1976), or replace the prior new-recombination (Tushman and Anderson, 1986). These provisions of technological opportunities surrounding the prior new-recombination may make the focal invention highly useful for subsequent technology developments. Hence, the exploration in searching for prior new-recombination within a local domain will increase the likelihood of developing technological breakthroughs.

Compared to a local search, a boundary spanning search for prior new-recombination leads to a lower likelihood for a focal invention to become a technological breakthrough. There are two reasons for this expectation. First, the focal invention that transports the prior new-recombination from the outside to the inside of a technology field may not effectively reduce the technological uncertainty of the prior new-recombination. Recall that standard procedures and methodologies along a specific technology trajectory facilitate the reduction of the uncertainty of new recombination within a local technology domain. Transporting prior new-recombination across boundaries makes it difficult to exploit the shared procedures and methodologies of a technology domain in tackling the uncertainty of the prior new-recombination (cf. Henderson and Clark, 1990)[12]. Take the example of the inkjet printer technology. When HP engineers examined new components outside their technology domain, they could not take advantage of their established selection processes, prototyping and testing procedures, and scientific methods (Fleming, 2002). As standard processes and methodologies in a technology field may not fully accommodate the prior new-recombination brought in from outside the technology boundary, understanding and interpreting unresolved/untested problems surrounding the prior new-recombination will thus be limited. Therefore, the resulting focal invention may be less useful for subsequent inventions.

[12] Henderson and Clark (1990) note that contextual changes render obsolete the "information-process structure" or "problem-solving strategy" in an established firm. Similarly, we submit that the standard procedure and methodology may not work with the contextual changes such as new integrations and links on a technology development trajectory.

Second, as a focal invention transports prior new-recombination from one to another technology context, the induced changes of new integrations and links around this prior new-recombination usually invoke “considerable confusion” in the field (Henderson and Clark, 1990). Inventors of subsequent inventions may be not convinced of the validity of those changes and thus hesitate to build on that focal invention (Sahal, 1985). Moreover, even if the focal invention would have destructive potentials by creatingnew integrations and links between technological components (Henderson and Clark, 1990), few subsequent inventions may immediately build on the focal invention because it is difficult for firms to recognize and evaluate this type of subtle changes in technological architecture (Henderson and Cockburn, 1994). Therefore, the focal invention that incorporates new integrations and links that were induced by a boundary spanning search for prior new-recombination has limited impacts on subsequent technology developments.

The recent ongoing development of the graphene photodetector provides an example for a boundary spanning search and the associated new integrations and links (Economist, 2012; Nature Nanotechnology, 2012). To create “the thinnest and most flexible detector in the world,” researchers actually combine the experimental quantum dot-graphene photodetector with standard silicon computer chip-processing techniques. Many have tried to overcome the barriers to a stable integration of photon (i.e., an element from the graphene photodetector technology) and electron (i.e., an element from the silicon chip technology), making some achievements, but none has yet to unequivocally succeed (Economist, 2012)[13]. A subsequent invention that can address the technological uncertainty around the newly generated integrations and links between photodetector and silicon chip technologies may well become a technological breakthrough for the graphene photodetector.

As a hybrid search includes both a local search and a boundary spanning search for prior new-recombination, it is likely to exhibit an intermediate effect on the likelihood that the focal invention becomes a technological breakthrough That is, the focal invention with a hybrid search reduces the technological uncertainty of the locally-searched prior new-recombination, thereby increasing its impact on future inventions; but it simultaneously creates new uncertainty from novel integrations and links associated with the prior new-recombination that is searched beyond the local boundary, thereby decreasing its usefulness for subsequent inventions. Therefore, a focal invention is most likely to become a technological breakthrough via a local search of prior new-recombination, and is least likely to become one through a boundary spanning search, with the likelihood through a hybrid search falling in between. Formally:

Hypothesis 2: When the technological search involves new recombination in prior inventions, the likelihood for the focal invention to become a technological breakthrough is greatest for a local search, smallest for a boundary spanning search, and intermediate

[13] "…As [Frank Koppens and his colleagues at the Institute of Photonic Sciences in Barcelona] describe in Nature Nanotechnology, they believe graphene can be used to make ultra-sensitive, low-cost photodetectors….Their purpose in doing so was to show that the technology meshes with the standard silicon-processing techniques used to make computer chips….Whether Dr. Koppens is the man to do it remains to be seen. But if he is, then he will certainly have justified the brouhaha that graphene has stirred up." (Economist, 2012; Konstantatos et al., 2012)

for a hybrid search, relative to that for an ordinary search that involves no prior new-recombination.

3 Methods

3.1 Data

We test these hypotheses using the data of U.S, patents in nanotechnology. We collected 1,848 nanotechnology patents granted to U.S. firms from 1980 to 2006, using the USPTO-entitled patents assigned to the class 977 (Nanotechnology). We downloaded the data from the USPTO website and parsed them, matching patent assignees with organization identifiers from the Nanobank (Zucker et al., 2007). U.S. patents or pre-grant publications can be classified into 977 as cross-references or secondary classifications (USPTO Classification Order 1850, 2005). To analyze patent citations, subclasses, and assignees, we utilized the Kauffman COMETS database (Zucker and Darby, 2011). Also, we identified 7,006 patent-cited year level observations.

The data construction also included the identification of (1) all patents that are cited by any of these 1,848 nanotechnology patents (i.e., backward citations); (2) 49,307,391 subclass pairs for the entire utility patents granted by 2008; and (3) the number of citations made by 2010 to the entire population of U.S. patents (i.e., forward citations).

3.2 Dependent Variables

We constructed the following three measures of outcome of technology developments.

3.2.1 Focal New-Recombination

We followed prior studies (e.g., Fleming, 2001) to define new recombination as the first-ever recombination of two subclasses that a nanotechnology patent establishes among the entire patent population granted by 2008. We then constructed a variable, *Focal New-Recombination*, that counts the instances of new recombination. Because subclasses allow us to examine fine-grained classifications of nanotechnology (Trajtenberg, Henderson, and Jaffe, 1997; Thompson and Fox-Kean, 2005), scholars increasingly focus on the subclass classification of patents to examine technology recombination (Fleming, 2001; Fleming and Sorenson, 2004; Fleming, Mingo, and Chen, 2007).

3.2.2 Focal New-Recombination within Nanotechnology

We separately identified focal new-recombination *within* the field of nanotechnology. We calculated the-first-ever recombination of two subclasses within the class 977. This is to examine our hypothesized effects on the "local" technology area.

3.2.3 Technological Breakthrough

The patent literature has established forward citations as an indicator of economic, social, and technological success of the patented technology (e.g., Trajtenberg, 1990; Harhoff et al., 1999; Fleming, 2001; Zucker et al., 2002; Fleming, Mingo, and Chen, 2010). Following this convention, we measured technological breakthroughs using forward citations. Specifically, we first generated the citation distribution of the entire population of U.S. patents (about 3.9 million) granted during 1976–2010. To account for differences in the citation hazard due to timing and technology, we used the residuals recovered by regressing the number of forward citations on patent class, application year, and grant year. This adjustment thus allows us to compare the number of forward citations across patents that were applied for and granted in the same year and in the same technology class. We then computed the z-score for each patent using these normalized forward citations. Finally, we defined *Technological Breakthrough* as an indicator variable that the patent belongs to the top 5% of the citation distribution (Singh and Fleming, 2010).

3.2.4 Forward Citation

To substantiate the mechanism by which a local search for prior new-recombination reduces technological uncertainty, we measured the change of technological uncertainty by counting the number of forward citation made each year to each nanotechnology patent.

3.3 Independent Variables

Our primary independent variables are the indicators of search types, as illustrated in Figure 2.1. For each type of search of prior new-recombination, we constructed the indicator as follows. . We first identified all patents that introduce a first-time combination of any two subclasses within the patent (i.e., new recombination). We then created for each U.S. firm nanotechnology patent a dummy variable that indicates if the patent cited any of the patents with the new recombination identified in the first step.[14]

[14] To illustrate the identification process for each quadrant, suppose that the focal patent cites a prior patent that has U.S. classes 977/1, 977/2, 400/3, and 400/4. The possible cases of subclass recombination are then (1,2), (1.3), (1,4), (2,3), (2,4), and (3,4). If none of these cases are new recombination, the focal patent belongs to the quadrant II. If only (1, 2) is new recombination, it belongs to III. If only (3, 4) is new recombination, it belongs to I. If one or more of (1,3), (1,4), (2,3) and (2,4) are new recombination, it belongs to IV.

This measure thus captures if a U.S. firm nanotechnology patent cites any prior invention that represents the first-time introduction of new recombination of a subclass pair.

To trace searches of prior knowledge, we use patent citations (Mowery et al, 1996; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Ahuja and Katila, 2004). We are aware of the concern that patent citations might be a noisy proxy for knowledge search due to, for instance, examiner-added citations (Alcacer and Gittelman, 2006). However, we submit that, even if the inventor of a patent were not aware of the prior art that the examiner separately added as patent references, these citations still represent the existence of related prior knowledge. Thus, assuming that inventors also search and use the existing knowledge from sources including patents, we consider patent citations as a reasonable proxy for knowledge search.[15]

3.3.1 Prior Ordinary-Recombination

We constructed a dummy variable, *Prior Ordinary Recombination*, that takes '1' if the focal patent did not cite any patents that incorporate new recombination, and '0' otherwise. This variable thus corresponds to the quadrant II in Figure 2.1.

3.3.2 Prior New-Recombination with Local Search

We constructed a dummy variable, *Prior New-Recombination within Local Search*, that takes '1' if the focal patent cited any patents that incorporate only new recombination within nanotechnology (USPTO class 977), and '0' otherwise. That is, we first identified the first-time introduction of the new recombination of subclass pairs

[15] Our results are robust to the exclusion of examiner-added citations.

within 977 and then excluded the cases that also involve a boundary spanning search for prior new-recombination. This variable thus corresponds to the quadrant III in Figure 2.1.

3.3.3 Prior New-Recombination with Boundary Spanning Search

We constructed a dummy variable, *Prior New-Recombination with Boundary Spanning Search*, that takes '1' if the focal patent cited any patents that incorporate new recombination in classes other than 977, and '0' otherwise. Similarly in the above variable, we excluded the cases that also involve a local search for prior new-recombination. This variable thus corresponds to the quadrant I in Figure 2.1.

3.3.4 Prior New-Recombination with Hybrid Search

Prior New-Recombination with Hybrid Search takes '1' if any of the prior patents that the focal patent cited incorporates new recombination both within and outside 977 (i.e., conducted both a local search and a boundary spanning search). This variable thus corresponds to the quadrant IV in Figure 2.1.

3.3.5 Post-Local Citation

This is a dummy variable, defined for the nanotechnology patents in our sample, that turns on for the period after the patent was first-ever cited by another nanotechnology patent.

3.4 Control Variables

3.4.1 Intensity of Local search

Each nanotechnology patent shows a different degree of searching for prior nanotechnology. Because the extent to which a patent searches local technologies affects forward citations (Rosenkopf and Nerkar, 2001), we controlled for the differences in the intensity of local search by including the share of the citations to nanotechnology patents among total backward citations.

3.4.2 All Backward Citations

We further included the total number of backward citations to control for the differences in the reliance on prior art.

3.4.3 Exploration-exploitation mix

Because the degree of exploration exhibits an inverted U-shape relationship with the technological performance (Nerkar, 2003; Rothaermel and Alexandre, 2009; Kotha et al., 2011; Uotila et al., 2013), we controlled for the exploration-exploitation mix. The dummy variable, *Exploration-exploitation mix,* indicates if the focal patent cites nanotechnology patents and non-nanotechnology patents simultaneously.

3.4.4 Prior new-recombination with self-citation

We added a dummy variable, *Prior New-recombination with self-citation*, that indicates if the focal patent cites any patent with prior new-recombination by the same assignee. This variable thus captures the effect of prior new-recombination that was introduced and cited by the same firm. This also controls for the potential effect from differences in organizational boundary in search (Rosenkopf and Nerkar, 2001).

3.4.5 Non-patent References

We included the number of non-patent references to control for the effect of searching for scientific knowledge, particularly given this construct's high correlation with future citation measures (Ahuja and Katila, 2004; Fleming and Sorenson, 2004).

3.4.6 Claims

The number of claims controls for the effect of patent claims on the dependent variables. As claims represent the coverage of protection for a patent, we expect that patents with more claims are likely to receive more forward citations.

3.4.7 Citation Age

We included the age of backward citations to control for the potentially diminishing effect of prior art. *Citation Age* may capture a "recency" effect on our dependent variables because temporal gap from prior art generally shows a high correlation with future citations (Nerkar, 2003). More important, citation age will control for the endogenous reduction of technological uncertainty over time, which we argue affects the likelihood of a technological breakthrough. We measure *Citation Age* by calculating the median of application years of all patents cited by the focal patent.

3.4.8 Recombination Age

We also controlled for the aging effect of recombination by including *Recombination Age*. We constructed this variable by calculating the median age of all recombination pairs of subclasses that the focal patent incorporates. This variable thus indicates how "old" the set of recombination that the focal invention draws on is on average. Recall that our argument on the mechanism through which a boundary spanning search achieves greater focal new-recombination is over and above the simple logic that recombination may get exhausted more quickly within a local domain. Hence, we expect *Recombination Age* to control for the exhaustion effect of recombinant components over time.

3.4.9 Year Fixed Effects

We included grant year dummies to control for the temporal effects in the development of nanotechnology.

3.4.10 Technology Category Fixed Effects

Nanotechnology spans multiple technology areas (NSTC 2011). Thus, we included technology category dummies to capture the effect of different technology subfields of nanotechnology. For technology categories, we used Zucker and Darby's (2011) patent categorization system that assigns each U.S. patent to one of five broad science areas (i.e., Biology/Chemistry, Semiconductor, Computer Science, Other Science, and Other Engineering).

3.4.11 Firm Fixed Effects

In some of the robustness check, we further included firm fixed effects to account for the inter-firm heterogeneity in technological capabilities.

Table 2.1 reports summary statistics of all variables and the matrix of correlations among them.

3.5 Estimation Methodology

We used three different regression methods for estimation, depending on the data type of the dependent variable: a negative binomial regression for models with a count-based dependent variable; a logit regression for models with a binary dependent variable; and an OLS regression for models with a continuous dependent variable (robustness checks). In all models, we report robust standard errors that are clustered by firm.

4 Results

4.1 Previews

Before presenting the results, we show the patterns in the raw data without controls. Figure 2.2 presents the distribution of focal new-recombination across the four quadrants according to the types of search, as defined in Figure 2.1. Compared to those with no new recombination, focal inventions that generate new recombination exhibit a much greater portion of a boundary spanning search . In contrast, only a very small portion of these focal inventions involves a local search, compared to the focal inventions with no new recombination. Figure 2.3 illustrates the distribution of technological performance, measured by the standard-normalized number of forward citations, across the four quadrants in Figure 2.1. In the graph, a local search is associated with a significantly fatter right tail of the distribution; relative to this local search, a boundary spanning search exhibits a much thinner right tail. Though only illustrative, the patterns shown in these figures are indeed consistent with our hypotheses.

Insert Figures 2.2 and 2.3 about here

4.2 Main Results

We now turn to the regression results. Models 1 and 2 in Table 2.2 test our hypothesis on focal new-recombination. In Model 1, the coefficients on search types generally show the order between search types that is consistent with our prediction. The coefficients on both the boundary spanning search and the hybrid search show significantly positive effects, while that on the local search is indistinguishable from zero (though positive). Based on the incidence rate ratio, relative to an ordinary search, a boundary spanning search increases the number of focal new-recombination by 57% and a hybrid search increases it by 43%, while a local search exhibits no advantage over an ordinary search in generating new recombination. The results get stronger for the local search and weaker for the boundary spanning search if we restrict the domain of new recombination to nanotechnology (Model 2). The rate of change in the number of focal new-recombination by search type is in the order of a hybrid search (115%), a boundary spanning search (100%), an ordinary search (baseline), and then a local search (-51%). In Model 2, Wald test demonstrates that the coefficient of the local search is significantly smaller than those of the boundary spanning search ($p<0.01$) and the hybrid search ($p<0.01$); but the coefficient of the boundary spanning search is not significantly different from that of hybrid search. Hence, Hypothesis 1 is partially supported. Among the control variables, the intensity of local search is in general negatively correlated with focal new-recombination and so is the total number of backward citations. Recombination age is significantly negatively related to focal new-recombination. Overall, the results are consistent with our hypothesis that focal new-recombination is most likely to result from a boundary spanning search and is least likely to arise from a local search.

Models 3 and 4 test our prediction on technological breakthroughs. The results confirm the hypothesis: the coefficients on search types are all positive and also significant (except that of the boundary spanning search), with the magnitude of effect consistent with the predicted order. In Model 3, using marginal effects based on logit coefficients[16], the likelihood of a technological breakthrough is highest for a local search (35%), followed by a hybrid search (21%), and is the lowest for a boundary spanning search. The Wald test demonstrates that the coefficient of the local search is significantly greater than those of the hybrid search ($p<0.05$) and the boundary spanning search

[16] To compute marginal effects, we used Stata command 'margins, dy/dx' after logit estimation.

(p<0.01); the coefficient of the hybrid search is greater than that of the boundary spanning search (p<0.05). Together, these results fully support Hypothesis 2. Further controlling for focal new-recombination, which has been shown to affect the propensity of a technological breakthrough (e.g., Fleming, 2001), does not change the results (Model 4).

We argued earlier that it is through the reduction of technological uncertainty surrounding prior new-recombination that searching and incorporating the prior new-recombination increases the likelihood for the focal invention to become a technological breakthrough. If a first-ever incorporation of prior new-recombination into the focal patent indeed reduces the technological uncertainty associated with that prior knowledge, we should expect more future inventions to start citing this original component, not to mention of the focal patent that addresses the uncertainty (as is already shown in Models 3 and 4 in Table 2.2). In particular, we expect the effect to be stronger for a locally-cited prior new-recombination. The analysis in Table 2.3 corroborates this proposed mechanism, by examining the citation patterns for nanotechnology patents. The unit of analysis in this analysis is patent-cited year. Model 1 shows that citation counts for a patent jump after the patent is cited by another nanotechnology patent for the first time, as indicated by the positive coefficient on *Post-local cited* variable. Model 2 indicates that patents that generate new recombination receive greater citations, though the coefficient seems imprecisely estimated. Model 3 reveals that the citation jump following the first-time citation by another nanotechnology patent is significantly greater for patents that generate new recombination. This suggests that any citation advantage that may accrue to a patent with new recombination comes from being cited by another “local” invention, which clears the uncertainty that has lingered around that original technology. Therefore, our proposed mechanism leading to Hypothesis 2 appears to be reasonably substantiated.

The results reported in Table 2.2 generally remain robust to additional controls of unobserved time-invariant heterogeneity across firms (Table 2.4). Overall, these firm-fixed effects seem to absorb significant variations, thereby reducing the precision of estimates. In Model 1, the coefficients on search types lose significance while the coefficient of a control variable, *Self-citation to PN*, turns significantly positive. Model 2 shows that the order between search types is consistent with our prediction but only the local search remains significantly negative. . The results on technological breakthroughs also turn much weaker, though the order of effect is consistent with those in previous analysis (Models 3 and 4). In particular, the coefficient on the local search remains strongly positive, while that on other search type loses significance. The weakening of these results appears mainly due to the much smaller number of observations in each model (as firms with only a few patents get dropped), which may have considerably reduced variations in the dependent variable.

Insert Table 2.1, 2.2, and 2.3 about here

4.3 Robustness Checks

We also performed a number of variations of the analysis to ensure the robustness of our results.[17] First, we controlled for the total number of prior new-recombination and

[17] Results of these additional tests are unreported due to space constraints but are available from the authors.

obtained the same results. Second, we estimated negative binomial and OLS regressions by using the count of new recombination and the standard-normalized number of forward citation as dependent variables. For the independent variables, we employed the total number of prior new-recombination of subclasses pairs within local search and boundary spanning search. The results showed robustness: the number of prior new-recombination with a boundary spanning search had a greater and significant effect than that with a local search on the number of focal new-recombination; and the number of prior new-recombination with a local search had a greater and significant effect than that with a boundary spanning search on the standard-normalized number of forward citations. Third, we redefined a boundary spanning search as novel recombination of a subclass pair that consists of one subclass from nanotechnology and another subclass from outside nanotechnology.[18] This is to address a potential concern that cross-boundary recombination should be considered as a boundary spanning search, rather than a hybrid search. With these alternative measures, we re-estimated models in Table 2.2. The results were robust to this alternative classification.

Finally, we repeated the analysis after excluding from backward citations all patent references that were added by the examiner. With these modified measures of search, our results remained robust. However, this alternative specification is incomplete because the examiner-added citation data are available only for the patents filed after 2001, while our sample covers 1980-2006.

[18] For example, the combination (2,3) from footnote 14, which was classified as a hybrid search, now belongs to this alternative measure of a boundary spanning search.

In sum, these various alternative tests show that our results are not driven by some particulars of the empirical design such as variable definition, sample coverage, and model choice.

5 Discussion and Conclusion

The purpose of this paper is to examine how new recombination contributes to the development of technological breakthroughs. We find that the likelihood of focal new-recombination and technological breakthroughs is a function of both search content (i.e., prior new-recombination) and search boundary (local vs. boundary spanning). Our findings characterize that first-ever new recombination in prior inventions (i.e., an original technology component) contributes more to developing technological breakthrough when searched locally, but is more conducive to generating new recombination when searched across boundaries. The results thus highlight the value of a local search, which has been generally considered less important than a boundary spanning search, of prior new-recombination in technology developments.

There are a few caveats to our findings, however. First, in identifying the search of prior art, we did not distinguish the source of citations. Thus, our citation measures include both firm citations and examiner-added citations (Alcacer and Gittelman, 2004). Following literature (Mowery et al., 1996; Rosenkopf and Nerkar, 2001; Ahuja and Katila, 2004), we believe that this measure still reasonably proxies for technological search. Even if the inventor filing a patent did not themselves search the examiner-added prior art, these patent references still indicate the existence of related prior technological components; this piece of technology is likely to have been searched by the inventor from sources other than patent documents. Our additional test also showed that our results held robust to the exclusion of available examiner-added citations. Nevertheless, we acknowledge the possibility that more data on external citations could project a different shape to our results. Second, related to the first point, we could not account for other channels through which firms may also search for technological components. For instance, consultants, customers, or suppliers have been identified as important sources of information for firm R&D (Cohen, Nelson, and Walsh, 2002; Roach and Cohen, 2012). Searches through those channels may not be reflected in patents citations. Thus, by only examining patent data, we may have omitted search efforts for knowledge from these different sources.

The differential effect between search types on focal new-recombination may be subject to an alternative interpretation. That is, the difference in their effects may simply come from differences in available technological components and exhaustion rate, rather than from the inherent advantage of a boundary spanning search in generating new links and integrations across boundaries as we argue. However, we believe that the greater positive effect of a boundary spanning search relative to that of a local search is beyond the effect of the relatively faster exhaustion of available components within a local domain. Note that our analysis controls for this exhaustion effect over time through *Intensity of local search* and *Recombination age*. If the exhaustion effect purely drove our results on focal new-recombination, the differences between search types should disappear with these controls. Our results show that the differences between search types in focal new-recombination survive the controls of exhaustion effect.

This study extends prior research on new recombination and technological breakthroughs, thereby claims three contributions to the literature. First, we conceptually distinguish new-recombination that is searched from new-recombination that is generated, and empirically test the effect of "for-search" exploration on "for-generate" exploration. This test provides strong evidence that for-search exploration does not automatically imply for-generate exploration and the relationship between the two is highly contingent on the context of search. Second, the measure of prior new-recombination allows us to identify a fine-grained level mechanism of how new recombinant knowledge (Fleming, 2001) determines the propensity that a focal invention becomes a technological breakthrough. We show that new recombination can contribute to the development of technological breakthroughs by being searched and assimilated locally, even though the very invention that introduces the new recombination may not necessarily become a technological breakthrough. Third, we provide evidence that local searches can also facilitate the development of technological breakthroughs, in fact more powerfully than boundary spanning searches do. By holding the level of exploration constant between boundaries of search, we show that search boundaries—local or boundary spanning—have distinct consequences on the technological development but their effects present a picture that is different from the well-established frame that favors a boundary spanning search as a driver of technological breakthroughs.

More specifically, our study offers alternative explanations for the relative efficacy of local and boundary spanning searches to those proposed in Rosenkopf and Nerkar (2001). Their findings strongly suggest that firms have to overcome localness in search in order to accomplish technological breakthroughs. In their study, a "boundary spanning search" has the highest impact, and a "local search" has the lowest impact, on the number of forward citations made to the focal invention (Rosenkopf and Nerkar, 2001). Our study offers different perspectives to the definition and role of local and boundary spanning searches, and the contrast in results may be reconciled by considering two major differences in the setup.

First, while their study covers all technological components as search targets, we focus only on searches of new recombination to control for differences in the degree of exploration. Second, differences in industry characteristics may generate differences in the impact of local and boundary spanning searches. Nanotechnology may be less "systemic" than the optical disc technology in Rosenkopf and Nerkar (2001). In the optical disc technology, firms must keep up with changes in other related technologies beyond their local boundary (ex. DVD players), and this catch-up is critical for subsequent inventions. In nanotechnology, however, this systematic relationship with outside of the local boundary is weaker. For instance, from the standpoint of carbon nanotube or nanowire research, the discovery of graphene (Geim, 2009) would not be an immediate necessity for a catch-up. In the same vein, the two technologies are in different stages of the lifecycle. Relative to the optical disk technology at the time of Rosenkopf and Nerkar's (2001) study, nanotechnology still remains an emerging and much less commercialized technology (NSTC, 2011). We suspect that, in a technology field with a lower degree of commercialization, complementary technologies are still underdeveloped and hence searching for those technologies outside the boundary may be less important. Our study complements Fleming (2001), who urged future work for empirical validation, by providing a test for new recombination as a source of technological uncertainty. We trace the path of recombination by examining prior new-recombination, which we find as an antecedent to focal new-recombination and technological breakthroughs. This implies that, while *focal* new-recombination may create technological uncertainty (Fleming, 2001), the technological uncertainty of *prior* new-recombination may decrease as focal inventions search and incorporate the prior new-recombination.

We also offer a complementary view to the literature that promotes a balanced approach to exploration and exploitation (Nerkar, 2003; Rothaermel and Alexandre, 2009; Kotha et al., 2011; Uotila et al., 2013). Studies in this literature have repeatedly demonstrated the inverted U-shape relationship between exploration, exploitation and firm performance. By holding the level of exploration-exploitation mix constant, we propose a microscopic view of the exploration, focusing on the intrinsic natures of local and boundary spanning searches. Our findings imply that, on any point of the inverted U-shaped line, a local search for prior new-recombination generates better outcomes in terms of technological breakthroughs, than do other types of search.

Our findings have a significant implication for technology and innovation strategies. Despite the literature's emphasis on the importance of new recombination, new recombination itself is not a rare instance, at least when measured by patents; Table 2.1 indicates that over 80% of nanotechnology patents include new recombination. However, new recombination seems to play a critical role in technology developments by influencing the likelihood of subsequent inventions becoming technological breakthroughs. It thus implies that firms should constantly explore the prior new-recombination to turn the original components into sources of a technological breakthrough. In other words, firms may introduce a novel technology component by incorporating prior new-recombination outside the technology field, and this novel technology component may then work as an input, by being locally searched and adopted, for a technological breakthrough.

Finally, from the managerial standpoint, our findings also speak to firm R&D managers who seek to achieve significant technology developments. Depending on the boundary of search—local or boundary spanning—searches of original technology components may exert differential impacts on focal inventions (i.e., increase the likelihood of creating a novel component or increase the likelihood of developing a technological breakthrough). Hence, R&D managers whose primary focus is on developing technological breakthroughs may focus on local searches of original technology and it may not be mandatory for them to extend the scope of technological search beyond their local domains. After all, our study highlights the importance of prior original technology components that enable R&D managers to attain superior technological outcomes, be it either through creations of novel technologies or through developments of technological breakthroughs.

6 References

Abernathy WJ, Utterback JM. 1975. A dynamic model of process and product innovation. Omega 3(6): 639–656.

Ahuja, G., and Katila 2004, R.. Where do resources come from? The role of idiosyncratic situations. Strategic Management Journal 25(8-9): 887-907.

Ahuja, G., Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22: 521–543.

Alcacer, J., & Gittelman, M. 2004. Patent citations as a measure of knowledge flows: The influence of examiner citations. The Review of Economics and Statistics 88(4): 774–779

Binnig, G., Rohrer, H., Gerber, Ch., and Weibel. E, 1982. Surface studies by scanning tunneling microscopy Physical Review Letters 49(1)

Brock, G.W., 2009. The second information revolution. Harvard University Press. Cambridge.

Burgelman, R. 1983. A process model of internal corporate venturing in a major diversified firm. Administrative Science Quarterly 28, 223-244.

Cohen, W.M., 2010. Chapter 4 – Fifty Years of Empirical Studies of Innovative Activity and Performance. Handbook of the Economics of Innovation 1:129–213

Cohen, W.M., Levinthal, D. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly 35(1): 128-152.

Cohen, W., Nelson, R., & Walsh, J. 2002. Links and impacts: The influence of public research on industrial R&D. Management Science 48(1): 1-23.

Dosi, G. 1982. Technological paradigms and technological trajectories—A suggested interpretation of the determinants and directions of technical change. Research Policy 11:147–162.

Economist. 2012. Optoelectronics. Graphene shows its colours. A much-vaunted new material may change telecommunications. May 12, 2012.

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science 47: 117–132

Fleming L. 2002. Finding the organizational sources of technological breakthroughs: the story of Hewlett Packard's thermal inkjet. Industrial and Corporate Change 11: 1059–1084.

Fleming, L., Mingo, S., Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly 52: 443–475.

Fleming, L., Sorenson, O. 2004. Science as a map in technological search. Strategic Management Journal Special Issue 25(8–9): 909–928.

Galunic C, Rodan S. 1998. Resource recombinations in the firm: knowledge structures and the potential for Schumpeterian innovation. Strategic Management Journal 19(12): 1193–1201.

Geim, A.K., 2009. Graphene: status and prospects. Science 324(5934): 1530-1534

Gerasimos. K. et al., 2012. Hybrid graphene–quantum dot phototransistors with ultrahigh gain. Nature Nanotechnology Published online

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. Journal of Economic Literature 28:1661-1707.

Griliches, Z. 1992. The search for R&D spillovers. The Scandinavian Journal of Economics 94: 29-47.

Hansen MT, Lovas B. 2004. How do multinational companies leverage technological competancies? Moving from single to interdependent explanations. Strategic Management Journal Special Issue 25(8–9): 801–822.

Harhoff, D., Narin.F, Scherer, F. M. and Vopel, K. 1999. Citation frequency and the value of patented inventions. The Review of Economics and Statistics 81(3): 511–515

Henderson, R.M. and Clark, K. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms, Administrative Science Quarterly 35: 9-30.

Jaffe, A. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. American Economic Review 76: 984–1001.

Kogut, B. & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science, 3(3): 383-397.

Konstantatos et al., 2012. Hybrid graphene–quantum dot phototransistors with ultrahigh gain, Nature Nanotechnology.

Kotha, R., Zheng, Y. and George, G. 2010. Entry into New Niches: The Effects of Firm Age and the Expansion of Technological Capabilities on innovative Output and Impact. Strategic Management Journal, 32: 1011-1024.

Klepper, S. 1997. Industry life cycles. Industrial and Corporate Change 6(1): 145–182.

Kuhn, T. S.1996. The Structure of Scientific Revolutions 3rd ed., Chicago: The Chicago University Press.

Levinthal DA, March JG. 1993. The myopia of learning. Strategic Management Journal, Winter Special Issue 14: 95–112.

March, J. 1991. Exploration and exploitation in organizational learning. Organization Science 2(1): 71–87.

March, J., Simon H. 1958. Organizations. Blackwell: Cambridge, MA.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, Winter Special Issue, 17: 77–92.

National Science and Technology Council. Committee on technology. Subcommittee on nanoscale science, engineering, and technology. 2011. National Nanotechnology Initiative Strategic plan. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

Nelson, R.R., Winter, S.G., 1977. In search of useful theory of innovation. Research Policy 6 (1), 36–76.

Nelson, R., Winter, S. 1982. An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Nerkar A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. Management Science 49(2): 211–229.

Podolny, J. M., Stuart, T. E. 1995. A role-based ecology of technological change. American Journal of Sociology 100 1224–1260.

Roach, M, Cohen, W. 2012. Lens or Prism? A Comparative Assessment of Patent Citations as a Measure of Knowledge Flows from Public Research. Management Science forthcoming

Rothaermel, F.T., Alexandre, M.T. 2009. Ambidexterity in technology sourcing: The moderating role of absorptive capacity. Organization Science, 20 (4): 759-780.

Romer, Paul M. 1994. Economic Growth and Investment in Children. Daedalus CXXIII: 141-154.

Rosenberg N. 1976. On technological expectations. Economic Journal 86(343): 523–535.

Rosenberg, N. 1996. Uncertainty and technological change. R. Landau, R. Taylor, G. Wright, eds. The Mosaic of Economic Growth. Stanford University Press, Stanford, CA.

Rosenkopf, L., Nerkar, A. 2001. Beyond local search: Boundary spanning, exploration, and impact in the optical disc industry. Strategic Management Journal 22(3): 287–306.

Sahal, D. 1985. Technological guideposts and innovation avenues. Research Policy 14 61–82.

Schumpeter, J. 1939. Business Cycles. McGraw-Hill Book Company, Inc.: New York.

Schumpeter, J. 1975. Capitalism, Socialism, and Democracy. Harper and Row Publishers: New York.

Simon, Herbert A. 1985. What we know about the creative process. In R. L. Kuhn (ed.), Frontiers in creative and Innovative Management 3-20. Cambridge, MA: Ballinger.

Simonton, D. K.1999. Origins of Genius: Darwinian Perspectives on Creativity. New York: Oxford University Press.

Simonton, D.K. 2004. Creativity in Science: Chance, Logic, Genius, and Zeitgeist. Campbridge University Press, UK.

Singh, J., Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? Management Science 56(1): 41-56.

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

Thompson, P., Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: A reassessment. American Economic Review 95(1): 450-460

Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovations. Rand Journal of Economics. 21 172–187.

Trajtenberg, M., Henderson, R., & Jaffe, A. 1997. University versus corporate patents: A window on the Basicness of Invention. Economics of Innovation and New Technology 5: 19-50.

Tushman, M., & Anderson, P. 1986. Technological Discontinuities and Organizational Environments, Administrative Science Quarterly, 31: 439-465.

Uotila J, Maula M, Keil T, Zahra S. A. 2009. Exploration, exploitation, and financial performance: analysis of S&P 500 corporations. Strategic Management Journal 30(2): 221-231.

Utterback, J.1971. The process of technological innovation within the firm. Academy of Management Journal 12: 75-88.

Weitzman, M.L. 1998. Recombinant growth. Quarterly Journal of Economics 113: 331–360.

Zucker, L.G., Darby, M.R., Armstrong, J. 2002. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. Management Science 48(1): 138-153.

Zucker, L., Darby, M., Furner, J., Liu, R., & Ma, H. 2007. Minerva unbound: Knowledge stocks, knowledge flows and new knowledge production. Research Policy 36(6): 850-863.

Zucker, L.G., Darby, M.R., 2011. COMETS Data Description, release 1.0, Los Angeles, CA: UCLA for International Science, Technology, and Cultural Policy, July 1, 2011.

Table 2.1 Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) PN with boundary spanning								
(2) PN with hybrid search	-0.805							
(3) PN within local search	-0.145	-0.061						
(4) Number of focal new-	0.070	-0.06	-0.027					
(5) Number of focal new-recombination within nano	0.011	-0.02	-0.032	0.210				
(6) Technological breakthrough	-0.083	0.124	0.043	0.023	0.087			
(7) Focal new-recombination	0.176	-0.204	-0.098	0.165	0.150	0.027		
(8) Intensity of local search	-0.373	0.471	0.191	-0.138	-0.092	0.030	-0.395	
(9) Exploration-exploitation mix	-0.214	0.393	-0.071	-0.033	-0.039	0.091	-0.102	0.273
(10) PN with self-citation	-0.024	0.151	0.016	0.005	-0.073	0.028	-0.008	0.111
(11) All backward citation	-0.076	0.187	-0.043	0.053	-0.043	0.096	0.005	-0.067
(12) Non-patent reference	-0.104	0.157	-0.025	0.044	0.002	0.110	0.052	-0.079
(13) Claims	0.059	-0.015	0.008	0.046	-0.015	0.073	0.01	-0.036
(14) Recombination age	0.053	-0.07	-0.011	-0.216	-0.322	-0.158	-0.149	0.004
(15) Citation age	0.157	-0.14	-0.06	0.074	-0.011	-0.1	0.082	-0.312
Obs	1848	1848	1848	1848	1848	1848	1848	1848
Mean	0.657	0.253	0.011	10.38	1.005	0.228	0.842	0.252
Std. Dev.	0.475	0.435	0.104	27.382	2.608	0.420	0.365	0.341
Min	0	0	0	0	0	0	0	0
Max	1	1	1	938	32	1	1	1

	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(9) Exploration-exploitation mix							
(10) Self-citation to PN	0.207						
(11) All backward citation	0.225	0.177					
(12) Non-patent reference	0.138	0.074	0.672				
(13) Claims	0.042	-0.015	0.144	0.125			
(14) Recombination age	-0.029	0.019	0.017	-0.019	0.003		
(15) Citation age	-0.105	-0.019	0.117	0.039	-5E-04	0.081	
Obs	1848	1848	1848	1848	1848	1848	1777
Mean	0.377	0.330	16.552	13.285	23.744	10.91	5.786
Std. Dev.	0.485	0.4702	29.320	32.835	18.714	7.409	3.448
Min	0	0	0	0	1	0	-1
Max	1	1	306	358	180	32	27

Notes: All correlation coefficients above 0.045 or below -0.045 are significant at 5%. PN stands for Prior new-recombination.

Table 2.2 The Effect of Prior New-Recombination on Focal New-Recombination and Technological Breakthrough (Baseline: Ordinary Search)

	(1) New Recomb nbreg [IRR]	(2) NanoNew Recomb nbreg [IRR]	(3) Tech Breakthrough logit [marginal effect]	(4) Tech Breakthrough logit [marginal effect]
PN with boundary spanning search (a)	0.448***	0.695***	0.932**	0.918**
	(0.170)	(0.184)	(0.456)	(0.453)
	[1.565]***	[2.004]***	[0.144]**	[0.142]**
PN with hybrid search (b)	0.357*	0.767***	1.325**	1.311**
	(0.186)	(0.265)	(0.519)	(0.520)
	[1.429]*	[2.154]***	[0.205]**	[0.202]**
PN with local search (c)	0.049	-0.720**	2.279***	2.278***
	(0.388)	(0.326)	(0.351)	(0.359)
	[1.051]	[0.487]**	[0.353]***	[0.353]***
Focal new-recombination				0.309
				(0.204)
Intensity of local search	-1.393***	-0.194	-0.542**	-0.418
	(0.161)	(0.188)	(0.251)	(0.264)
Exploration-exploitation mix	0.037	0.065	0.399***	0.400***
	(0.090)	(0.131)	(0.142)	(0.143)
Self-citation to PN	0.154*	-0.200*	-0.130	-0.142
	(0.081)	(0.117)	(0.146)	(0.146)
All backward citation	0.000	-0.004*	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.003)
Non-patent reference	-0.001	0.000	0.006**	0.006**
	(0.002)	(0.002)	(0.003)	(0.003)
Claims	0.002	0.000	0.008**	0.008**
	(0.002)	(0.002)	(0.004)	(0.004)
Recombination age	-0.084***	-0.173***	-0.022**	-0.019**
	(0.007)	(0.011)	(0.009)	(0.009)
Citation age	0.011	0.004	-0.079***	-0.078***
	(0.010)	(0.018)	(0.026)	(0.025)
Constant	2.699***	1.891***	-4.362***	-4.718***
	(0.210)	(0.229)	(0.780)	(0.811)
Technology fixed effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Wald-test ($\chi 2$)				
H0: a=c	0.94	19.37	13.97	15.15
	(p=0.333)	(p=0.0000)	(p=0.0002)	(p=0.0001)
H0: a=b	0.85	0.16	5.13	5.01
	(p=0.356)	(p=0.686)	(p=0.024)	(p=0.025)
H0:b=c	0.55	15.45	5.68	6.16
	(p=0.459)	(p=0.0001)	(p=0.017)	(p=0.013)
Log-likelihood	-5722.1	-1937.2	-865.9	-864.6
N	1841	1841	1830	1830

* p<0.10 ** p<0.05 *** p<0.01. Robust standard errors clustered by firm in parentheses. Incident Rate Ratio (Model 1 and 2) or Marginal effect (Model 3 and 4) reported in square brackets. The dependent variable for Model 2 (Nano new recomb) stands for Focal new-recombination within nanotechnology. PN stands for Prior new-recombination.

Table 2.3 Post-Local Citation and Technological Uncertainty

	(1)	(2)	(3)
nbreg		Number of Forward Citation	
Post-local cited	0.549***		0.410***
	(0.036)		(0.069)
Focal new recomb		0.098	-0.035
		(0.066)	(0.080)
Post-local X New recomb			0.165**
			(0.078)
Intensity of local search	-0.246***	-0.116	-0.204***
	(0.069)	(0.078)	(0.074)
All backward citation	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Non-patent reference	0.005***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)
Claims	0.004**	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Constant	-0.092	0.278***	-0.094
	(0.080)	(0.101)	(0.112)
Year fixed effects	Yes	Yes	Yes
Technology category fixed effects	Yes	Yes	Yes
Log-likelihood	-16216.8	-16442.3	-16208.4
N	7006	7006	7006

* p<0.10 ** p<0.05 *** p<0.01. Robust standard errors clustered by patent in parentheses. The unit of analysis is patent-cited year. The results are conditional on the patents being at least once locally cited.

Table 2.4 The Effect of Prior New-Recombination on Focal New-Recombination and Technological Breakthrough with Firm Fixed Effect (Baseline: Ordinary Search)

	(1)	(2)	(3)	(4)
	New Recomb nbreg	Nano New Recomb nbreg	Tech Breakthrough logit	Tech Breakthrough logit
PN with boundary spanning search (a)	0.087	0.268	1.073	1.068
	(0.150)	(0.243)	(0.748)	(0.748)
PN with hybrid search (b)	0.078	0.299	1.292	1.285
	(0.175)	(0.292)	(0.844)	(0.845)
PN with local search (c)	0.124	-1.058***	2.079***	2.074***
	(0.309)	(0.341)	(0.524)	(0.522)
Focal new-recombination				0.110
				(0.288)
Intensity of local search	-1.233***	-0.004	-0.591*	-0.555
	(0.157)	(0.204)	(0.347)	(0.400)
Exploration-exploitation mix	0.077	0.065	0.329*	0.330*
	(0.098)	(0.151)	(0.196)	(0.196)
Self-citation to PN	0.176**	-0.164	-0.367*	-0.370**
	(0.083)	(0.207)	(0.191)	(0.189)
All Backward Citation	-0.002	-0.001	-0.001	-0.001
	(0.003)	(0.004)	(0.006)	(0.006)
Non Patent Reference	-0.001	-0.008	0.006	0.006
	(0.002)	(0.006)	(0.006)	(0.006)
Claims	0.003	0.003	0.009	0.009
	(0.002)	(0.004)	(0.005)	(0.005)
Recombination age	-0.086***	-0.164***	-0.036**	-0.035**
	(0.008)	(0.013)	(0.014)	(0.015)
Citation age	-0.004	-0.014	-0.103***	-0.102***
	(0.010)	(0.022)	(0.031)	(0.031)
Constant	4.108***	0.746	-3.766***	-3.912***
	(0.420)	(0.604)	(1.171)	(1.244)
Year fixed effect	Yes	Yes	Yes	Yes
Technology category fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Wald-test ($\chi 2$)				
H0: a=c	0.02	26.41	3.69	3.80
	(p=0.896)	(p=0.0000)	(p=0.055)	(p=0.051)
H0: a=b	0.03	0.02	0.76	0.74
	(p=0.870)	(p=0.8809)	(p=0.382)	(p=0.388)
H0:b=c	0.03	33.52	1.56	1.60
	(p=0.870)	(p=0.0000)	(p=0.212)	(p=0.206)
Log-likelihood	-5139.9	-1639.9	-513.7	-513.6
N	1841	1841	1141	1141

* p<0.10 ** p<0.05 *** p<0.01. Robust standard errors clustered by firm in parentheses. PN stands for Prior new-recombination. Application year dummies are used for nbreg models to obtain convergence.

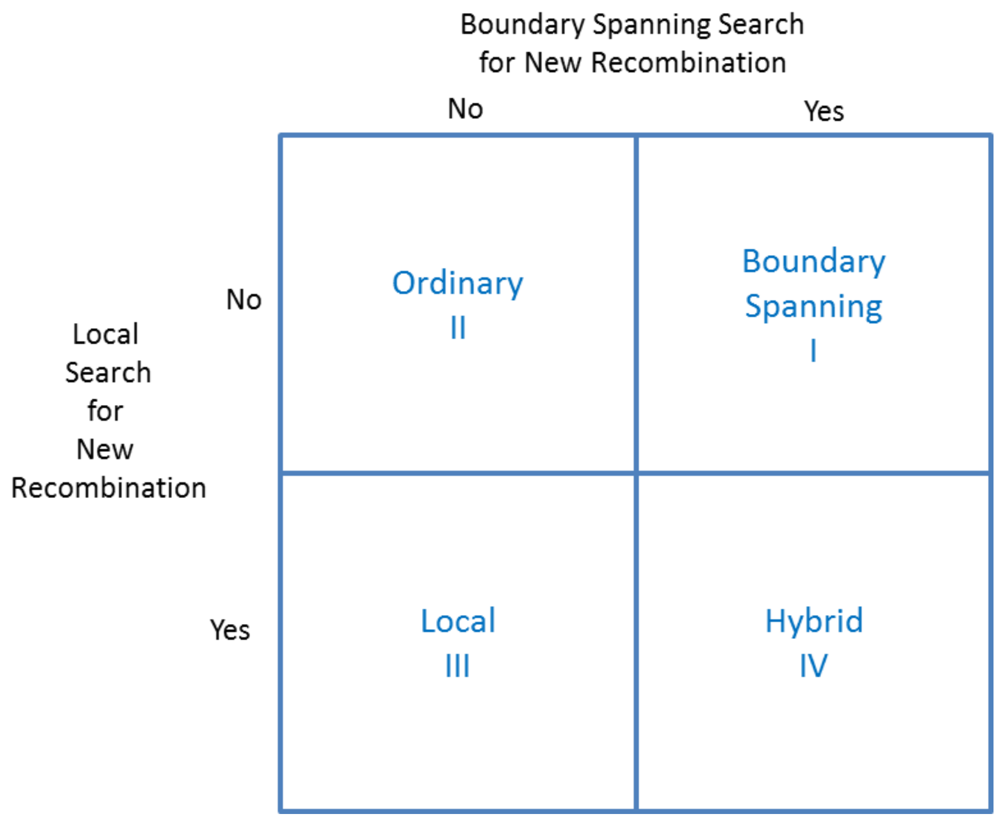
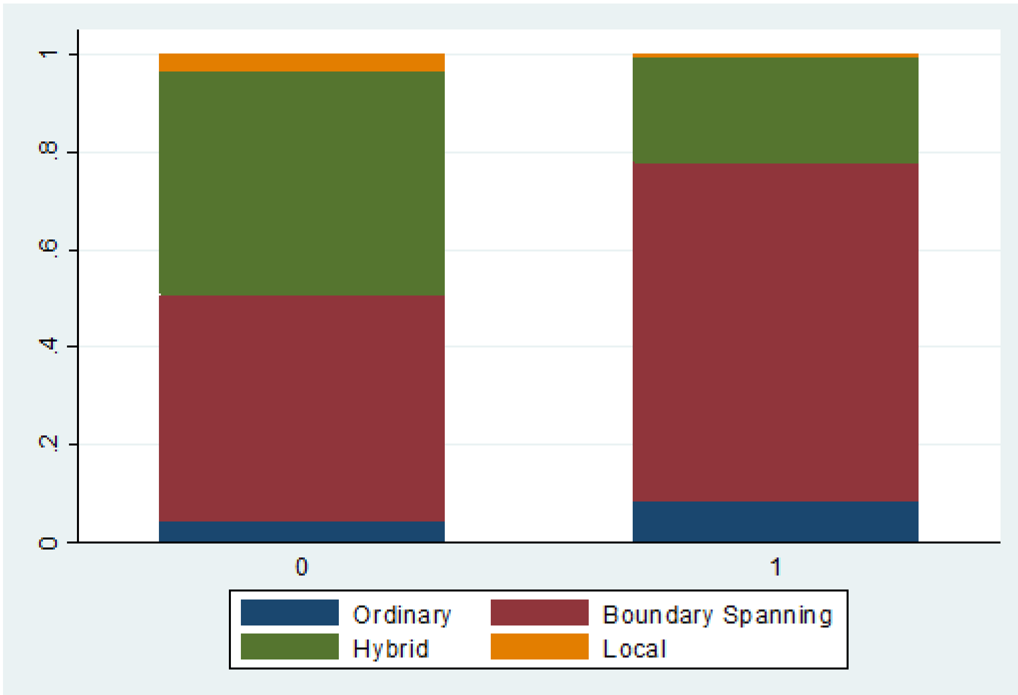
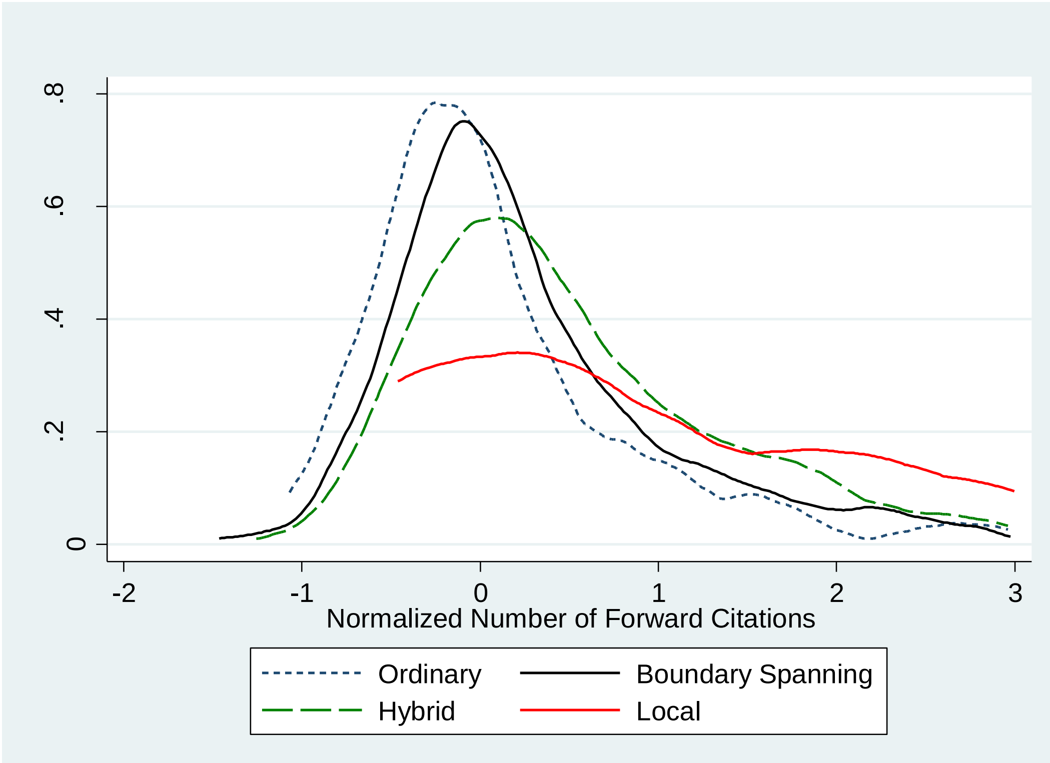


Figure 2.1 Types of Search of New Recombination



Note. 0: Non focal new-recombination; 1: Focal new-recombination

Figure 2.2 Focal New-Recombination by Types of Search of Prior New-Recombination



Note. The citations are winsorized at 0.1%.

Figure 2.3 Distribution of Technological Performance by Types of Search of Prior New-Recombination

CHAPTER 3

DO KNOWLEDGE FLOWS TRIGGER INTERFIRM COOPERATION?

EVIDENCE FROM THE ENTERPRISE SOFTWARE INDUSTRY

1 Introduction

A strong body of literature argues that interfirm cooperation stimulates knowledge flows. Whether operationalized in terms of strategic alliance (Mowery, Oxley, and Silverman, 1996; Rosenkopf and Almeida, 2003; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), strong ties in networks (Uzzi, 1997), formal inter-organizational networks (Owen-Smith and Powell, 2004), or the social proximity of actors in networks (Sorenson, Rivkin, and Fleming, 2006), it is apparent that interfirm cooperation is an important mechanism that promotes knowledge flows. Interfirm cooperation induces knowledge flows by overlapping firms' technological knowledge (Mowery, Oxley, and Silverman, 1996), facilitating the learning process (Rosenkopf and Almeida, 2003), or by increasing mutual trust between cooperating firms (Uzzi, 1997; Sorenson, Rivkin, and Fleming, 2006, 2006).

While the specifics of knowledge flows resulting from interfirm cooperation—technology transfer (Mowery, Oxley, and Silverman, 1996; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), flows of fine-grained information (Uzzi, 1997), the search for new knowledge (Rosenkopf and Almeida, 2003), knowledge spillover through a conduit (Owen-Smith and Powell, 2004), or flows of complex knowledge (Sorenson, Rivkin, and Fleming, 2006, 2006)—are diverse, in general the literature that studies the effect of interfirm cooperation on knowledge flows assumes that interfirm cooperation is exogenous to knowledge flows between firms. However, this assumption is debatable because knowledge may flow before the formation of interfirm cooperation. Despite the potential effect of preceding knowledge flows on firms' propensity to interfirm cooperation, little is known as to how knowledge flows affect the formation of interfirm cooperation. By failing to explicitly examine the effect of knowledge flows on interfirm cooperation, understanding the relationship between interfirm cooperation and knowledge flows remains incomplete.

The effect of knowledge flows on the formation of interfirm cooperation is an intriguing problem because, while advantageous access to knowledge may motivate firms to pursue strong interfirm cooperation (Mowery, Oxley, and Silverman, 1996; Uzzi, 1997; Kogut, 1988; Gulati, 1998), interfirm cooperation may be accompanied by the risk of expropriation (Teece, 1986; Williamson, 1991). To fill this gap, I address the following question: What aspects of knowledge flows lead firms to, or hinder firms from, the formation of interfirm cooperation?

I focus on the conditions under which interfirm cooperation is formed, by drawing on a growing body of literature that examines the mechanisms that drive interfirm cooperation. Stuart (1998) concludes that firms' technologically proximal positioning in a high-technology market determines the propensity to strategic alliance. Similarly, Mowery, Oxley, and Silverman (1998) find that a technological overlap between firms induces interfirm cooperation. Rosenkopf, Matiu, and George (2001) discuss the ways in which industry-level technical committees increase subsequent alliance formation. Cassiman and Veugelers (2002) contend incoming knowledge spillovers and appropriability increase firms' research and development (R&D) cooperation. As well, firms cooperate through licensing when licensing-out partners signal strong knowledge-transfer capabilities (Ceccagnoli and Jiang, 2013).

Adding to this line of research, this paper aims to contribute to the literature by unraveling the antecedent of interfirm cooperation in knowledge flows. In examining knowledge flows, I develop two novel approaches. First, I note that the conflation of codified knowledge and tacit knowledge causes part of the difficulty in explaining the triggering effect of knowledge flows on interfirm cooperation. To resolve this issue, I draw on the classic distinction between codified knowledge and tacit knowledge (Polanyi, 1966; Nelson and Winter, 1982; Kogut and Zander, 1992; Nonaka, 1994; Adler, 1996). While codifications of knowledge is processed by reduction and conversion that allows less costly transmission and reproduction of information, tacit knowledge is related to know-how or expertise that can be transferred by personal demonstration and instruction (Polanyi, 1966; Nonaka, 1994; Adler, 1996). Because codification speeds up knowledge flows (Zander and Kogut, 1995; Nonaka, 1994), codified knowledge may be transferred faster than tacit knowledge. I begin with the consideration that, while the trading of tacit knowledge requires embedded and direct relationships (Von Hippel, 1988; Uzzi, 1997; Almeida, Song, and Grant, 2002; Cowan, Jonard, and Zimmermann, 2007), codified knowledge flows can precede, and thus affect, the formation of interfirm cooperation.

Second, I characterize knowledge flows as directional. Knowledge flows between two firms may have two directions that show asymmetries (Knott, Posen, and Wu, 2009). While scholars have studied knowledge transfer, sharing, and exchange, they usually focus on a dyadic-level analysis in which bidirectional knowledge flows are assumed (cf. Mowery, Oxley, and Silverman, 1996; 1998; Gomes-Cassares et al., 2006). Thus, the implications of directional knowledge flows remain undeveloped. To better understand knowledge flows, I extend prevailing models of knowledge flows to describe the asymmetry of directional knowledge flows that may unequally affect the firms' propensity to interfirm cooperation.

To tackle the effect of knowledge flows on interfirm cooperation, I consider a specific knowledge network in which codified knowledge flows take place between a center firm and periphery firms. In general, a knowledge network consists of a center firm that provides foundation or platform technologies and periphery firms that develop independent and complementary technologies by communicating knowledge with the center firm (Stuart, 1998; Ahuja, 2000). There exist different degrees of interfirm cooperation between the center and each periphery firm.

I propose that codified knowledge flows weaken the formation of interfirm cooperation between a center and a periphery firm, by mitigating the need for tacit knowledge. Notice that I make a distinction on whether codified and tacit knowledge flows are complements or substitutes. While literature has assumed that codified and tacit knowledge flows are complements after interfirm cooperation (Mowery, Oxley, and Silverman, 1996; Almeida, Song, and Grant, 2002), they could be substitutes before interfirm cooperation (Dasgupta and David, 1994; Zollo and Winter, 2002). I also contend that technological uncertainty in codified knowledge flows from a periphery firm hinders a center firm from pursuing interfirm cooperation because the center firm cannot calculate the obsolescence risk of the uncertain technology. In contrast, uncertainty in codified knowledge flows from a center firm may induce a periphery firm to pursue interfirm cooperation because the periphery firm can resolve the uncertainty through collaborative troubleshooting.

A knowledge network in the enterprise software industry is a nice setting for this study. The enterprise software industry is a “complex product industry” (Cohen, Nelson, and Walsh, 2000) where technology consists of numerous components, many of which often build on other firms’ technologies. Thus, a knowledge network in the enterprise software industry may include significant and abundant interfirm knowledge flows, presenting a fertile ground to examine knowledge flows. I perform a statistical analysis on a sample of 243 enterprise software firms involved in the knowledge network centered on Oracle between 1992 and 2009. Oracle is one of the largest platform providers in the enterprise software industry.[19] By analyzing codified knowledge flows (measured by patent citations), uncertainty in codified knowledge flows (measured by technological distance between cited and citing patents), and interfirm cooperation (identified through examining the context of news wire), I find supports for my hypotheses. The results show that on the likelihood of the formation of interfirm cooperation, 1) directional codified knowledge flows have a negative effect; 2) technological uncertainty in codified knowledge flows from a periphery to center firm has a negative effect; and 3)

[19] “Oracle is one of the world’s leading enterprise software companies. The company provides database, middleware software, and application software as well as related services. It has a robust market share in most of the markets it serves. The company leads the relational database management systems (RDBMS) market with a share of 48.6 percent in 2007, compared to 47.9 percent in 2006.The company was the second largest player in the enterprise resource planning (ERP) software market and a leading player in the customer relationship management (CRM) market. In 2008, the company continued to maintain its market position.” (Global application Software-Industry Profile, Datamonitor, 2007; Oracle Corporation-Company Profile, Datamonitor, 2009)

technological uncertainty in codified knowledge flows from a center to a periphery firm has a positive effect.

2 Theory and Hypothesis

2.1 Motivating Case Study: The Enterprise Software Industry

The enterprise software industry exemplifies the general features of knowledge flows and interfirm cooperation in a knowledge network. By interviewing the industry experts and examining industry documents and patents, I submit a concrete example of the interfirm cooperation and knowledge flows between a software vendor, such as Nsoft or Psoft, and a platform provider, such as Oracle.[20] Nsoft, founded in 1994, provides software that can complement Oracle products. In 1996, Oracle and Nsoft first announced that they would work together to provide an enhanced analysis of data generated and stored in Oracle applications.[21] Through this cooperation, Nsoft provided a new product that enabled non-technical end users to view easily critical application data by automating the process of extracting data from the Oracle application. According to Nsoft, "It does work in about two hours that would take many man-months to do manually."[22] Nsoft and

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[20] I use pseudo names for periphery firms.
[21] LexisNexis Business Wire Service, 1996. "Oracle enhances the Discoverer/2000 analysis of Oracle application data; Oracle and Nsoft Corp. team to deliver new products to present valuable financial and manufacturing data in an intuitive end user display."
[22] CRN, 2001. Nsoft's nets software billed as data 'traffic cop.' http://www.crn.com/news/channel-programs/18835909/noetixs-nets-software-billed-as-data-lsquo-traffic-cop-rsquo.htm (Accessed on September 20, 2010)

Oracle have repeated their cooperation to meet changes in the related technology field over the last 10 years.[23]

From the perspective of a periphery firm such as Nsoft, it is critical to understand detailed information regarding where and how the underlying data schema is stored in Oracle products (CRN, 2001). The main knowledge sources for understanding Oracle technology are cooperative work with Oracle developers, users of Oracle products, the Oracle conferences, and Oracle products and documents. Among these sources, working together at the developer level is a unique way to access Oracle technology because this cooperative work provides a direct channel to communicate with Oracle developers. For instance, to ensure compatibility between the Oracle and Nsoft products, technical engineers from both firms work alongside each other for a certain period. Through this type of cooperative work, Oracle technology that is not shown in a codified format can be accessed. Not only the periphery firms, such as Nsoft, but also the platform provider, Oracle, can take advantage of the cooperative work similarly by accessing the partners' expertise in industry-specific technologies (e.g., the banking, telecommunication, or semiconductor industry solutions) or in specialized technologies (e.g., security, storage, or hardware).

Three things can be inferred from this cooperative work. First, the knowledge communicated through working together at the engineer or developer levels can be tacit in that the knowledge is embedded in individual engineers as expertise. Second, the

[23] LexisNexis Business Wire Service, 2002. "Nsoft Announces Alliance With Oracle-Companies Commit To Improved Reporting For Applications Customers"; 2007. "Nsoft Achieves Oracle Certified Advantage Partner Status"; 2009. "United States: Nsoft Introduces Nsoft Analytics for Oracle E-Business Suite"

knowledge communication renders meta-knowledge that points out how, what, and where to codify to achieve compatibility effectively and efficiently. While a part of meta-knowledge can be codified, the knowledge on how to integrate and link the scattered knowledge can be tacit. And third, the codified knowledge reflects inner technologies that may be codified but hidden. For instance, the source code is codified somewhere but never open even to inside engineers. Obtaining these types of knowledge has been the best benefit of interfirm cooperation from the standpoint of technology development.

This style of interfirm cooperation opens up an interesting approach for my study because the cooperative work channels tacit knowledge. While software products, conferences, and documents are usually the sources of codified knowledge flows, the interfirm cooperation between individual developers or engineers may facilitate communicating tacit knowledge. Interfirm cooperation occurs in several forms: certifying and supporting partners' technology, licensing-in (e.g., Original Equipment Manufacturer) and licensing-out (e.g., embedded licensing of software), training and working with counterparts for a joint business opportunity (e.g., alliances), and working together to standardize technology (e.g., technology consortia). All of these types of interfirm cooperation have a common characteristic: that individual developers or engineers work together to achieve technological compatibility. While firms pursue the benefit of tacit knowledge through interfirm cooperation, both sides of the cooperation are usually concerned about expropriation risks because they know that once know-how or expertise is transferred, their counterpart can easily implement the corresponding technologies.

Another phenomenon of particular interest is ubiquitous codified knowledge flows in this industry. For instance, software, per se, represents the product of codification. To keep abreast of technological innovation, firms regularly search and monitor other firms' technologies through codified information, e.g., newly launched software,[24] conferences in the field of computer engineering and information technology, or patents. By utilizing available codified knowledge, until the necessity for cooperation is immediate, firms seem to deter or, at least, delay the formation of an interfirm cooperation that is likely to bear expropriation risks.[25] Considering that interfirm cooperation channels tacit knowledge, this delayed cooperation may imply a possibility that codified knowledge flows can take the place of tacit knowledge flows.

The case of patent filing by Psoft, a software vendor founded in 1987, illustrates that the presence of codified knowledge flows can be independent of interfirm cooperation. Psoft filed a patent in August 2002, citing an Oracle patent filed in 1998 months before Psoft had a chance to work with Oracle in December 2002, when it joined a technology consortium with Oracle.[26] These codified knowledge flows are directional

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[24] Newly launched software products generally provide codified knowledge in two ways: 1) various codified documents including user guides, implementation guides and entity relation diagrams (Zollo and Winter, 2002); 2) reverse engineering (Grimaldi and Torrisi, 2001). As an example of reverse engineering, the test of software functionality provides information about work flows, input or output data, and user interface. Also, the process of enterprise software implementation enables the understanding of how software works with hardware, middleware, and other software.

[25] Industry experts I interviewed remarked that firms are always watching technology developments in industry through available software or industry conferences, and are very careful to take their time when forming interfirm cooperation because they recognize the risk of information disclosure.

[26] LexisNexis Business Wire Service, 2002. "Momentum Builds As Eclipse Eco-System Grows; Consortium Grows To 30 Members In First Year; Four New Open Source Projects Form; Download Requests Top 3.1 Million—Eclipse is now supported by providers of a broad range of development technologies including specialists in modeling, code generation, metadata management, testing, embedded computing, enterprise middleware, collaboration, services, research and application systems vendors…"

in dyadic relations between Oracle and a periphery firm. For instance, in 1998 Nsoft filed a patent for the “Distributed Data Warehouse Query and Resource Management System,” which is strongly related to Oracle core technology, such as database management. This patent cites three Oracle patents filed in 1997 that involved the technology of “Summary Table Management in a Computer System.” Since Nsoft’s patent filing, Oracle has cited this Nsoft patent in its own new patents filed from 2001 to 2006. Assuming that patent citations reasonably reflect, though imperfectly, codified knowledge flows, this event of patent filing and citations implies that between Oracle and a periphery firm, intensity, timing, and direction of codified knowledge flows are asymmetric.

The knowledge flows and interfirm cooperation between Oracle and periphery firms are not unique phenomena in the enterprise software industry. In fact, the majority of knowledge networks based on a platform seem to experience similar knowledge flows and interfirm cooperation. The motivating case highlights several features of knowledge flows and interfirm cooperation: i) interfirm cooperation may represent communication of tacit knowledge; ii) codified knowledge may flow before interfirm cooperation; iii) firms experience directional asymmetric codified knowledge flows.

2.2 Interfirm Cooperation and Tacit Knowledge

Interfirm cooperation is defined as a voluntary arrangement between firms involving an exchange or sharing of products, technologies, or services (Gulati, 1998).This paper focuses on interfirm cooperation involving technical exchange or sharing. While the voluntary interfirm arrangements for technology innovation take various forms of cooperative work, including platform participation (Bresnahan and Greenstein, 1999), strategic alliance (Mowery et al., 1996), cooperation between manufacturers and users (Von Hippel, 1988, 1994), and industry consortiums for standard technology (Rosenkopf, Metiu, and George, 2001), they all may provide the opportunity for individual engineers to contact each other and share their technical expertise (Polanyi, 1966; Von Hippel, 1988, 1994). This expertise is associated with the tacit knowledge embedded in skilled engineers and technical systems (Zollo and Winter, 2002; Leonard-Barton, 1992). Thus, interfirm cooperation enables firms to communicate tacit knowledge. Without this interfirm cooperation, individual engineers may not be allowed to collaborate with other firms' engineers and thus tacit knowledge flows are less likely to occur. That is, interfirm cooperation is effective in promoting tacit knowledge flows (Cowan, Jonard, and Zimmermann, 2007).

In the enterprise software industry, interfirm cooperation may take place to achieve technological compatibility between a centrally positioned firm and other periphery firms in a knowledge network (Bresnahan and Greenstein, 1999; Chellappa and Saraf, 2010).[27] This interfirm cooperation is distinct in that the firms cooperate based on the center firm's technology platform—a bundle of standard components around which platform participants and users are organized (Bresnahan and Greenstein, 1999). For

[27] The interfirm cooperation between a center firm and periphery firms within a knowledge network in the enterprise software industry is analogous to that of the Toyota network. First, like Toyota's modular production system, in which partners improve their products without experiencing a disruption of integration with Toyota's platform (Spear and Bowen, 1999), enterprise software platforms support modular architecture with independent modules for integration points. Thus, while cooperating, the center firm and the periphery firms pursue their innovations independently. Second, as Toyota positions itself at the center of the network and shares tacit knowledge (Dyer and Nobeoka, 2000), the platform providers, such as Oracle in the enterprise software industry, have a central network position, providing knowledge for compatibility. A salient difference between the two networks is that, while Toyota supplies a consolidated final product and, thus, governs its knowledge network with strong authority (Makadok and Coff, 2009), a center firm within a knowledge network in the enterprise software industry provides independent but compatible products with periphery firms, focusing on communicating knowledge that allows independent software products to run as a system.

instance, firms such as IBM cooperate with periphery firms surrounding the IBM computer platform to capture outside innovations (Bresnahan and Greenstein, 1999), while periphery firms exploit the platform technology as well as provide complementary technologies (Huang et al., 2013).

2.3 Codified and Tacit Knowledge flow

Because firms aim to augment their knowledge (Kogut and Zander, 1992), knowledge flows exist among firms (Nelson and Winter, 1982) and affect further innovation (Cohen and Walsh, 2000). Spence (1984) and Jaffe (1986) assume that knowledge flows are symmetric, non-directional, and pooled, however, because firms manage knowledge flows heterogeneously in trying to maximize incoming knowledge flows and the appropriability of their knowledge, knowledge flows may become directional and asymmetric (Cassiman and Veugelers, 2002; Knott, Posen, and Wu, 2009). For instance, Cohen and Levinthal (1989) suggest that incoming knowledge flows that is absorbed can be asymmetric by introducing the interaction between the available outside knowledge pool and a firms' ability to identify, assimilate, and exploit knowledge from other firms. In addition to their ability to manage knowledge flows, the position of firms in a network may affect knowledge flows. Network theories propose that a central position in a network provides advantages to accessing information (Burt, 2004; Owen-Smith and Powell, 2004). Therefore, in a knowledge network, knowledge flows from a center firm to periphery firms, and vice versa, may show asymmetries.

These asymmetric knowledge flows may affect the firm's propensity to pursue interfirm cooperation. If pre-existing knowledge flows provide information that firms would otherwise pursue through interfirm cooperation, firms are likely to reduce forming interfirm cooperation. Specifically, codified knowledge flows can flow before interfirm cooperation because firms can search other firms' knowledge in codified formats regardless of interfirm cooperation. For example, patents can be one of the most important sources of knowledge flows even among rival firms because patenting requires the procedure of the codification and the disclosure of knowledge (Cohen et al., 2002). Compared to tacit knowledge that is related to know-how, expertise, or accumulated skills that are "sticky" to move (Von Hippel, 1988; 1994), the codified knowledge is easily transmitted and replicated (Kogut and Zander, 1992).

Literature has, in general, assumed that codified and tacit knowledge flows are complements in interfirm cooperation (Mowery, Oxley, and Silverman, 1996; Almeida, Song, and Grant, 2002): if codified knowledge flows are observed, tacit knowledge flows are present. However, codified knowledge flows may be distinguished from tacit knowledge flows before the formation of interfirm cooperation. I expect that codified knowledge can substitute tacit knowledge for two reasons.

First, codified knowledge can be particularly important in the enterprise software industry because software technology is inherently the product of codification and systemization. Codified knowledge is more adequate than tacit knowledge when it is used in a standardized, controlled context in which the whole knowledge system is reducible to a set of simple parts that relate to one another (Nelson and Winter, 1982). To the extent that these conditions hold, the role of codified knowledge may be disproportionally significant in developing technology (Nelson and Winter, 1982). The enterprise software industry agrees well with this condition because software technology can be standardized as well as consist of sub-modular parts. Thus, codified knowledge flows can play a significant role in capturing knowledge from other firms' technologies thereby being capable to act as a substitute for tacit knowledge flows (Dasgupta and David, 1994; Zollo and Winter, 2002).

Second, firms may pursue codified knowledge first before they seek tacit knowledge from other firms. Recall that while the sources of codified knowledge such as software products and related documents are available on the market, tacit knowledge is obtained through interfirm cooperation. Interfirm cooperation may generate the risk of expropriation or opportunism because firms exchange and share the knowledge about their proprietary technologies (Teece, 1986; Rosenkopf, Matiu, and George, 2001; Katila, Rosenberger, and Eisenhardt, 2008). The problem of expropriation risk arises because interfirm cooperation requires a certain part of tacit knowledge to be open to the counterpart (Rosenkopf, Matiu, and George, 2001). Codified knowledge can be protected by legal mechanisms, such as patents and copyrights; tacit knowledge, if not demonstrated, is difficult for other firms to expropriate. However, once tacit knowledge is transferred, the efficacy of legal instruments to protect the knowledge is low (Teece, 1986). Thus, firms may exploit codified knowledge flows first because tacit knowledge is more costly than codified knowledge. Considering that codification may make tacit knowledge explicit, despite a degree of "degradation" (Nonaka, 1994; Adler, 1996), obtained codified knowledge from a source may offset the need for tacit knowledge from that same source. Therefore, if codified knowledge flows increase, the expected role of tacit knowledge may decrease thereby weakening the need for interfirm cooperation.

Nevertheless, beyond a certain point, codified knowledge is not likely to replace tacit knowledge because knowledge-adopting firms may need specific expertise that remains in non-codified format. Tacit knowledge matters because knowledge has coherent aspects while codification may record only the part of the knowledge that fits into the codifying rules (Nelson and Winter, 1982). Although firms search and collect available codified knowledge about other firms' technologies, they may still need subtle and tacit knowledge about how to configure and adjust corresponding technologies more efficiently and sufficiently (Von Hippel, 1994). Thus, the role of codified knowledge to compensate the need for tacit knowledge may be weakened beyond a certain point. Hence, I hypothesize as follows:

Hypothesis 1: Greater flows of codified knowledge from a periphery firm to a center firm reduce the likelihood of interfirm cooperation between the center firm and the periphery firm within a knowledge network. The interfirm cooperation decreases at a decreasing rate until it levels off.

Hypothesis 2: Greater flows of codified knowledge from a center firm to a periphery firm reduce the likelihood of interfirm cooperation between the center firm and the periphery firm within a knowledge network. The interfirm cooperation decreases at a decreasing rate until it levels off.

2.4 Uncertainty induced by Codified Knowledge Flows

Codified knowledge flows may be asymmetric in bringing up uncertainty because codified knowledge flows transport technology components with different familiarities to knowledge-adopting firms. Under the assumption of bounded rationality, firms are likely to localize knowledge flows from external sources to the particular area of their prior knowledge (Cohen and Levinthal, 1990). Considering this path dependency (Nelson and Winter, 1982; Cohen and Levinthal, 1990), non-local knowledge components may cause uncertainty in the firms that recombine these unfamiliar components (Fleming, 2001). That is, when firms search and recombine knowledge components from distant technology, the outcome of new technology is uncertain. Thus, unfamiliar knowledge components, introduced by non-localized knowledge flows from distant technology, may induce uncertainty to a knowledge-adopting firm.

The extant literature indicates two different views of how uncertainty influences the formation of interfirm cooperation (Williamson, 1991; Kogut and Zander, 1992). One view suggests that under high uncertainty, governing interfirm cooperation may be costly to address the potentially unpredictable consequences of that uncertainty (Williamson, 1991). Unpredictable changes may ruin a specified asset achieved through interfirm cooperation, such as technological compatibility (Williamson, 1979). Thus, forming bilateral relationships becomes unfeasible. This implies that uncertainty is likely to negatively affect the formation of interfirm cooperation. Conversely, another view holds that uncertainty stimulates interfirm cooperation because in order to reduce the uncertainty driven by others, firms may seek knowledge embedded in other firms (Kogut and Zander, 1992). That is, technological uncertainty caused by distant technology may drive the formation of interfirm cooperation because the path dependency of firms' technology developments tends to deter internal development of the distant technology (Nelson and Winter, 1982; Cohen and Levinthal., 1990). Hence, uncertainty caused by distant knowledge flows can drive firms either to obviate the cost of bilateral relationships, thus leading to reducing the formation of interfirm cooperation, or to overcome the firm boundaries, thereby increasing the formation of interfirm cooperation. A center firm and a periphery firm that have stratified technological positions in a knowledge network may interpret technological uncertainty differently (Stuart, 1998; cf. Resenberg, 1996). This implies that to address technological uncertainty, the center and periphery firm may calculate the cost and benefit of interfirm cooperation from different standpoints.

A center firm, by adopting uncertain technology, can usually strengthen its centrality and, consequently, its power in a network because the actors who resolve uncertainty are identified as experts and are sought out by other players within a knowledge network (Burkhardt and Brass, 1990). Thus, the adoption of uncertain knowledge strengthens the technological prestige of a center firm within a knowledge network. However, there is a risk that the adopted uncertain technology will be obsolescent rather than dominant (Tushman and Anderson, 1986). It is likely difficult to calculate the risk of unfamiliar distant technology ex-ante. This risk may frustrate the center firm in pursuing interfirm cooperation with the periphery firm, the source of codified knowledge flows with technological distance because the risk of the uncertain technology may be greater when a center firm is more bound to the technology. Thus, the center firm is likely to cope with the risk of uncertain technology by being less bound to the source of uncertain technology (cf. Eisenhardt and Martin, 2000; Davis, Eisenhardt, and Bingham, 2009). Therefore, under the uncertainty introduced by adopting distant technology, while the center firm may utilize codified knowledge flows from the distant technology of a periphery firm, the center firm likely avoids the formation of interfirm cooperation with the periphery firm. I summarize the discussion as follows:

Hypothesis 3: Greater technological distance in knowledge flows from a periphery firm to a center firm reduces the likelihood of interfirm cooperation between the center firm and the periphery firm within a knowledge network.

Considering that increasing technological uncertainty results in increased communication among actors, leading them to build structures to interpret the uncertainty that they experience (Van de Ven, Delbecq, and Koenig, 1976), under technological uncertainty, periphery firms may form interfirm cooperation with a center firm. The interfirm cooperation benefits the periphery firm by taking advantage of collaborative problem solving (Uzzi, 1997). In adopting distant technology from a center firm, a periphery firm needs to communicate with a center firm to troubleshoot and evaluate the uncertainty that the distant technology will generate. These benefits of troubleshooting cannot be obtained through mere codified knowledge flows because know-how or expertise may be required to solve problems. Experts from the center firm can help a periphery firm solve problems within the setting of interfirm cooperation (cf. Uzzi, 1997).

Another important consideration for a periphery firm when forming interfirm cooperation under uncertainty can be the expropriation risk from a center firm. Recall that commercial relations are invariably calculative (Williamson 1993). When a periphery firm adopts distant knowledge components from a center firm, it may consider both the benefit and risk following interfirm cooperation. Calculating the risk of interfirm cooperation, a periphery firm may expect a low expropriation risk when it adopts knowledge flows from the distant technology of a center firm. The main reason for this expectation is that even if a periphery firm forms interfirm cooperation and communicates tacit knowledge, a center firm is not likely to move into the periphery firm's distant technology field. This is because the center firm lacks the prior knowledge necessary to exploit the distant technology, therefore facilitating opportunistic behavior, such as expropriation, is unlikely. Thus, from a periphery firm's standpoint, distant codified knowledge flows from a center firm may be a strong driver in pursuing interfirm cooperation because cooperating with a center firm may reduce the uncertainty that is caused by the center firm's distant technology without the expense of expropriation.

The previous arguments suggest that a periphery firm may pursue cooperation with a center firm when adopting uncertain technology from the center firm. However, interfirm cooperation is a dyadic agreement, thus it is important to discuss how uncertainty in distant knowledge flows from a center firm to a periphery firm increases the center firm's interest in interfirm cooperation. Because a center firm is not usually aware of the codified knowledge out-flows to a periphery firm, the effect of those knowledge flows on the center firm is secondhand rather than direct. When the periphery firm proposes to form interfirm cooperation with the center firm, the center firm will recognize the distant technology of the periphery firm. The center firm may be interested in the suggestion from the periphery firm for two reasons. First, by accepting the suggestion, the center firm can obtain a chance to test new applications of its technology. Second, as the second mover in negotiations for interfirm cooperation, the center firm has an advantageous position to observe the periphery firm's offers and then ensure agreeable conditions. Thus, the center firm likely agrees to form interfirm cooperation. Taken together, for each of these reasons—the benefit of understanding technological uncertainty and less risk of expropriation—technological uncertainty in codified knowledge flows from a center firm drives a periphery firm to form interfirm cooperation with the center firm. The following hypothesis summarizes the discussion:

Hypothesis 4: Greater technological distance in knowledge flows from a center firm to a periphery firm increases the likelihood of interfirm cooperation between the center firm and the periphery firm within a knowledge network.

3 Methods

3.1 Sample

I identified 2,560 firms that had codified knowledge flows with Oracle in the enterprise software industry from 1992 to 2009. This process began with 1,725 Oracle patents that had citing (forward citation) or cited (backward citation) relationships with those firms. I collected Oracle patents from 1976 in the United States Patent and Trademark Office (USPTO) patent database as Oracle was launched in 1977. The collected data show that Oracle filed its first patent in 1992. Among the 2,560 firms identified, I randomly selected 10 percent and collected annual data for those firms to test the hypotheses. This process resulted in a panel data that includes a total of 243 sample firms and 1,110 firm-year observations. I took this random sample to avoid autocorrelation (Fleming, Mingo, and Chen, 2009). Autocorrelation can be a problem because firms in a knowledge network of Oracle may have unobserved similarities. Hence, observations of firms can be correlated. The 10 percent random sampling may reduce the concern that statistically correlated firms will be included together in the estimation.

3.2 Dependent Variables

3.2.1 Formation of interfirm cooperation.

I measured the formation of interfirm cooperation between Oracle and a periphery firm for each year by examining Lexis/Nexis news wire announcements, including those about teaming for co-work, alliances, partnerships, formation of forums, consortiums for standardizing and integrating technologies, supporting each other's technologies, and achieving certification. These terms are all used to express the formation of interfirm cooperation by article reporters, and the core of the technical activities is achieving technological compatibility. To identify the formation of interfirm cooperation, I first searched the news releases using search terms regarding both Oracle and firms that cited Oracle or that were cited by Oracle and then I examined the contexts of the news releases to determine whether there was interfirm cooperation. The identified years of the formation of interfirm cooperation spanned from 1984 to 2010. Finally, for each firm-year observation, I constructed a variable that is equal to the number of the formation of interfirm cooperation between Oracle and the corresponding periphery firm.

3.3 Independent Variables

3.3.1 Codified knowledge flows from a periphery to a center firm/ Codified knowledge flows from a center to a periphery firm.

I measured the codified knowledge flows by using the number of patent citations. Because my interest is in the directional codified knowledge flows, I distinguished the number of citations by Oracle to a periphery firm and the number of citations by a corresponding periphery firm to Oracle. For codified knowledge flows from a periphery firm to a center firm, I used the number of citations by Oracle patents (backward citation); for codified knowledge flows from a center to a periphery firm, I used the number of citations by a corresponding periphery firm's patents (forward citation). Using these backward and forward citations, I identified two separate directions of codified knowledge flows. For each year between Oracle and a periphery firm, I constructed the independent variables of codified knowledge flows for each direction using the total number of backward or forward citations during previous five-year moving windows. The choice of a five-year period is consistent with Jiang, Tan, and Thursby (2010), Ahuja and Lampert (2001), and Griliches (1984) regarding the effectiveness of knowledge diffusion.

As I use patent citations, I am aware of the concern that patent citations might be a noisy proxy for knowledge flows because citations include examiner-added citations (Alcacer and Gittelman, 2006). Nevertheless, drawing on literature (Mowery, Oxley, and Silverman, 1996; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), I consider that patent citations can reasonably act as a proxy for codified knowledge flows in this study. This is because a firm may have searched codified knowledge carried in sources (e.g., available software products or industry documents) other than patent files but may fail to cite the corresponding prior-art if the existence of prior-art patent is not well known. Examiner-added citations may reduce this type of miss-identification because they enable tracing the existence and ownership of related knowledge that might flow but not be recorded. Another concern in using patent citations as a proxy for knowledge flows emerges because citations exclude knowledge flows through direct interfirm communications (Roach and Cohen, 2012). However, this exclusion may eventually justify the use of patent citations as a meaningful proxy for codified knowledge flows because this study intends to distinguish codified knowledge flows from tacit knowledge flows. Thus, as patent citations may not represent "non-codified" knowledge flows (Roach and Cohen, 2012), they well agree with the characteristics of codified knowledge flows, which is precisely what this study examines.

3.3.2 Technology distance in knowledge flows from a periphery to a center firm/ Technology distance in knowledge flows from a center to a periphery firm

I identified technological distance on codified knowledge flows using the USPTO patent classes. I computed the technological distance of codified knowledge flows following Jaffe's (1986) measure of technological proximity. I calculated technological distance longitudinally as it changes over time (Jiang, Tan, and Thursby, 2010). First, I calculate technological distance for each year between Oracle and a periphery firm:

$$\text{Technological distance} = 1 - F'_{it}F_{jt} / (F'_{it}F_{it})^{1/2}(F'_{jt}F_{jt})^{1/2}$$

Fit is a dimension vector representing 473 USPTO patent classes of firm *i*'s patents that firm *j* cited at time *t*. Fjt is a dimension vector representing 473 USPTO patent classes of firm *j*'s patents that cited firm *i*'s patents at time *t*. I measured technology distance in codified knowledge flows from a periphery to a center firm when *i* represents 243 sample firms and *j* represents Oracle and measured technology distance in codified knowledge flows from a center to a periphery firm when *i* represents Oracle and *j* represents 243 sample firms. Second, constructing technology distance in codified knowledge flows from a periphery to a center firm or vice versa for each firm-year observation, I used the greatest technology distance that a focal firm (i.e., Oracle or a periphery firm) experienced in codified knowledge flows for the previous five years. When the number of codified knowledge flows is zero for five-year windows, I assumed that technology distance is the greatest and assigned '1' to the technology distance measure, building simultaneously a dummy variable that indicates a zero number of codified knowledge flows.[28]

3.4 Control Variables

3.4.1 Prior interfirm cooperation

I included an endogenous occurrence of interfirm cooperation, operationalized as the number of prior interfirm cooperation between a center firm and a periphery firm (Stuart, 1998). I used the past five-year experiences to control the endogenous concern for the effect of prior experience of interfirm cooperation.[29]

3.4.2 Firm age

Rothaermel and Boeker (2008) suggest that firm age affects the formation of interfirm cooperation. To capture this effect, I included firm age measured as the time since founding. Firms whose names have changed were traced to original names to identify the founding year.

3.4.3 Acquisition

I controlled for whether firms were acquired by other firms to capture the effect of acquisition on the formation of interfirm cooperation. I would expect the acquired firms to be weakened in their managerial actions, such as forming interfirm cooperation.

3.4.4 Platform technology shift

I controlled for an environmental factor by including a dummy variable that indicates the years when Oracle shifted platform technologies. There were relatively

[28] I checked robustness by using alternative measures for technology distance and obtained similar results.
[29] I also tried three-year experiences for robustness checks and obtained very similar results.

radical technological changes in platforms:[30] changes to client/server environment in 1985, supporting OLTP (Online Transaction Processing) in 1989, the first application software launching in 1990, supporting the Internet environment in 1995, embracing the JAVA programming language in 1998, supporting open standard technology XML and Linux in 1999, and embracing hybrid technologies instead of pursuing pure Oracle-owned technology in 2005. It would be expected that these technological shifts in the platform affect possible technologies that can be compatible with the platform and, thus, affect the formation of interfirm cooperation.

3.4.5 Bidirectional knowledge flows

I included the existence of bidirectional knowledge flows. This control variable is to capture the effect of bidirectional knowledge flows on forming interfirm cooperation that literature has depicted (Mowery, Silverman, and Oxley, 1998). I constructed a dummy variable that indicates the co-existence of two directional knowledge flows (i.e., from a periphery to a center firm and vice versa).

3.4.6 Patent stock of a periphery firm/Patent stock of a center firm

Because I constructed codified knowledge flow measures using patent citations, I controlled for the patent stock that a periphery firm and a center firm possesses to isolate the effect of patent-based constructs on the formation of interfirm cooperation (Rothaermel and Boeker, 2008). In the context of this paper, a periphery firm and a center firm have a dyadic relationship, and, thus, the relative size of the patent stock of dyadic

[30] Oracle's 30th Anniversary. http://www.oracle.com/us/corporate/history/index.html (Accessed on 20 Sep 2010)

firms matters. I measured the patent stocks for each year as the ratio of the patent stock of two dyadic firms.

3.4.7 Industry consolidation

This industry experienced two major merges, the Oracle-Peoplesoft merge in 2005 and the Oracle-BEA merge in 2009. Oracle aggressively drove these mergers, which signaled a hostile acquisition (Peoplesoft merge) and a new market entry (BEA merge) to current and potential partners. Thus, I would expect that these events kept periphery firms from the formation of interfirm cooperation. I included a dummy variable that indicate the years of these industry consolidation events.

3.4.8 Year fixed effects

I controlled for environmental factors that varied over time but that were constant across firms by including year-effect dummy variables. I grouped three years as a period to control year effects.

3.4.8 Firm fixed effects

To capture the effect of unobservable heterogeneity of firm, I incorporated firm-effect dummy variables.

Table 3.1 provides summary statistics of these variables and the correlations between them. A pair of two codified knowledge flows (i.e., from center to periphery firm and vice versa) variables exhibits a correlation that is high enough to cause concern regarding multicollinearity. Hence, in the estimation model, I included each codified knowledge flow separately and then together to show that the effects of two codified knowledge flows are not due to the collinearity between them.

Insert Table 3.1 about here

3.5 Estimation

I operationalized the dependent variable as the number of interfirm cooperation formed between Oracle and a periphery firm within the Oracle knowledge network in each year. Hence, the observations present a firm-year panel. I report fixed effect Poisson models with heteroskedasticity-robust standard error. Poisson regression assumes that the event count is drawn from the single parameter Poisson distribution:

$$\Pr(\mathrm{Y_{it}} = \mathrm{y_{it}}) = \frac{\exp(-\lambda_{it})\,\lambda_{\mathrm{it}}^{\mathrm{y^{it}}}}{\mathrm{y_{it}}!}$$

where the parameter λ is the mean and the variance of the event count and y is a non-negative integer count variable capturing the number of instances of interfirm cooperation. The standard assumption is $\lambda_{it} = \exp(x'_{it}\beta)$. As robustness checks, I also estimated using logit and OLS models. I applied the following specification:

$$\begin{aligned}\mathrm{D.V}_{t1,i} = f\big(\varepsilon_{t1,i};\ \alpha 1_i + \alpha 2_{t1} & + \beta_1 \mathit{Codified\ Knowledge\ Flows\ from\ Periphery\ to\ Center}_{t2,i} \\ & + \beta_2 \mathit{Codified\ Knowledge\ Flows\ from\ Center\ to\ Periphery}_{t2,i} \\ & + \beta_3 \mathit{Technology\ Distance\ from\ Periphery\ to\ Center}_{t2,i} \\ & + \beta_4 \mathit{Technology\ Distance\ from\ Center\ to\ Periphery}_{t2,i}\big)\end{aligned}$$

where $\alpha 1_i$ is the firm fixed effect, $\alpha 2_{t1}$ is the year fixed effect, β_1, β_2, β_3, and β_4 are the coefficients to be estimated for time lagged independent variables, and $\varepsilon_{t1,i}$ is the error term.

To address the issue of unobserved firm heterogeneity that is correlated with the dependent variable in the panel data, I adopted fixed-effect estimators. The fixed-effect panel approach permits analysis of the cause and effect without strong assumptions (Cameron and Trivedi, 2005). With the fixed-effect estimators, I incorporated the estimation with heteroskedasticity-robust standard errors. The obtained robust standard errors can reduce not only the concern for heteroskedasticity, but also a potential problem of serial correlation that the fixed-effect estimation may include in the error term (Woodridge, 2002).

4 Results

4.1 Main Results

Table 3.2 presents results from the fixed effect Poisson regression models that investigate the effect of codified knowledge flows on interfirm cooperation. For the baseline analysis, Model 1 contained control variables only, and Models 2 through 8 included each direction of codified knowledge flows independently and together.

Insert Table 3.2 about here

I found support for Hypothesis 1 in Models 2, 5, and 7; the parameter estimate for codified knowledge flows from a periphery to a center firm was significantly negative. Model 5 and 7 also supported the nonlinear effects of codified knowledge flows from a periphery to a center firm on the number of interfirm cooperation, showing that a quadratic term for codified knowledge flows from a periphery to a center firm was significantly positive.

Models 3, 6, and 7 supported Hypothesis 2; the parameter estimate for codified knowledge flows from a center to a periphery firm was significantly negative. Model 6 supported the nonlinear effects of codified knowledge flows from a center to a periphery firm on the number of interfirm cooperation, showing that a quadratic term for codified knowledge flows from a center to a periphery firm was significantly positive. The quadratic term in Model 7 lacks significance while showing positive effect.

Model 8 supported Hypothesis 3; the parameter estimate for technology distance in knowledge flows from a periphery to a center firm was significantly negative, indicating that an increase in technological distance in codified knowledge flows from a periphery to a center firm decreases the number of interfirm cooperation.

Model 8 also supported Hypothesis 4; the parameter estimate for technology distance in knowledge flows from a center to a periphery firm was significantly positive, indicating that the number of interfirm cooperation increases with technological distance in codified knowledge flows from a center to a periphery firm.

To facilitate the interpretation of estimates, I calculated the magnitude of changes in the dependent variable by a unit change in independent variables.[31] According to the parameter estimate, in Model 7, a unit increase in codified knowledge flows from a periphery to a center firm decreased the number of interfirm cooperation by 2.1 percent; a unit increase in codified knowledge flows from a center to a periphery firm decreased the number of interfirm cooperation by 5.6 percent, holding other factors constant. In terms of technology distances (Model 8), when the technology distance of codified knowledge flows from a periphery to a center firm increases from “0” to “1”, the number of interfirm cooperation decreased by 66 percent; when the technology distance of codified knowledge flows from a center to a periphery firm increased from “0” to “1”, the number of interfirm cooperation increased by 864 percent.

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[31] I computed the incidence-rate ratio (IRR) after fitting the corresponding model.

4.2 Robustness Check

To ensure the robustness of the results, I performed a number of variations of the analysis. Table 3.3 presents the results for estimating a fixed-effect logit model using a new binary dependent variable, which measures the event of interfirm cooperation. The main results continued to hold, except the statistical significances lacked for codified knowledge flows from a periphery to a center firm in Model 2, codified knowledge flows from a center to a periphery firm in Model 3, and the quadratic term of codified knowledge flows from a center to a periphery firm in Model 6.

Insert Table 3.3 and 3.4 about here

Also, table 3.4 presents the robust results of estimating an OLS model incorporating a firm fixed-effect and robust variance estimator. In general, the main results continued to hold, except the quadratic term of codified knowledge flows from a center to a periphery firm and vice versa weakened the statistical significance in Model 6.

Insert Table 3.5 - 3.8 about here

In the main specification, I controlled year fixed effect by grouping three years as a period to recover the effects of time relevant control variables such as platform technology shift and industry consolidation. To ensure the robustness of the result, I included year dummies, excluding those control variables. The results showed robustness for Poisson fixed effect estimations in general except that the parameter estimate of codified knowledge flows from a periphery to a center firm lacked significance in Model 2 (Table 3.5). Also, the results of logit fixed effect regressions demonstrated robustness in general except that the parameter estimate of codified knowledge flows from a center to a periphery firm lacked significance in Model 7 and the quadratic term of codified knowledge flows from a center to a periphery firm lacked significance in Model 6 while the parameter estimate of technological distance of codified knowledge flows from a periphery to a center firm strengthened significance in Model 8 (Table 3.6). Finally, the results of OLS regressions with fixed effect showed robustness in general except that the parameter estimate of technological distance of codified knowledge flows from a periphery to a center firm lacked significance in Model 8 while parameter estimate of codified knowledge flows from a periphery to a center firm strengthened significance in Model 4, 6, and 8 (Table 3.7).

In general, Model 8 in Tables 3.2 through 3.4 show that the terms of two codified knowledge flows lacked significance by adding the two terms of technological distances in codified knowledge flows. This may raise a concern of a potential correlation between the natures of two measures: codified knowledge flows and technological distances of codified knowledge flows. Hence, I used an alternative measure for technological uncertainty: technological novelty. As novel technologies usually bring up uncertainty (Rosenberg, 1996), technological novelty can be a good alternative measure for technological uncertainty. However, it may be different from the technological distance measure in that novel technologies are not necessarily distant technologies. A first-ever recombination of two subclasses can be considered as inventing a novel technological component (Fleming, 2001). Following this convention, I measured technological novelty using the number of the new recombination of patent subclasses pairs that codified knowledge flows included during previous five-year moving windows. Table 3.8 reports robust results in general except that the test of novelty in codified knowledge flows from a center to a periphery lacked significance, though the sign was consistent with the prediction (Model 1 and 2). This indicates that technological novelty in codified knowledge flows from a center to a periphery firm may not reduce a periphery firm's concern for expropriation risks as much as technological distance in codified knowledge flows from a center to periphery firm does, thereby not increasing significantly the formation of interfirm cooperation.

As the USPTO issued a pro-software patent guideline in 1996, my sample period included a strong legal regime change that strengthened the patentability of software inventions (Cockburn and MacGarvie, 2011; Huang et al., 2013). For robustness check, I employed this institutional change to indicate the increase of overall codified knowledge flows. The result shows robustness in general (Table 3.6, Model 3). The parameter estimate for the post-period of the pro-software regime change was significantly negative, indicating that the increase of codified knowledge flows weakens the likelihood of interfirm cooperation, though the regime change represents the increase of overall codified knowledge flows instead of each directional codified knowledge flow.[32]

I performed additional multiple robustness checks.[33] I ran robustness analyses with alternative technology distances for observations with zero codified knowledge flows. First, I checked robustness by calculating the technology distance from codified knowledge flows at t+1 when the number of codified knowledge flows is zero at t during the past five years. The number of observations decreased to 179 in this model (number

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[32] In addition, this regime change may have impacted the results of my estimations that examine patent data. Hence, I ran a robustness check using only post-1996 data in the sample with the same models in Table 2. While the number of observations was reduced to 522 (number of firms = 60), the results showed robustness.

[33] Tables for these robustness tests are unreported due to space concerns but are available from the author.

of firms = 20). The main result remained robust. Second, I took technology distance as missing in zero codified knowledge flows. The model decreased to 144 observations (number of firms = 17), and the main result was robust in general, except the parameter estimate of technology distance in knowledge flows from a periphery to a center firm lacked statistical significance.

I tested whether the effect of codified knowledge flows is robust when "certifying partners" is excluded from the count of *formation of interfirm cooperation*. While interfirm cooperation represents tacit knowledge communication in this paper, the activity of certifying partners, a type of interfirm cooperation, can also be used to signal legitimacy in the market rather than to communicate tacit knowledge. Six instances of certifying partners were identified and excluded. The results continued to hold; the quadratic term of codified knowledge flows from a center to periphery firm weakened the statistical significance.

As shown in Table 1, the low mean of the dependent variable suggests that the dependent variable includes many zero values. Thus, a potential issue is that some firms are systematically out of contention for the formation of interfirm cooperation. Hence, I tested my predictions using zero-inflated Poisson models by controlling for the effect of each firm on the zero inflation. The result showed robustness in general. The only change was that in Model 2, codified knowledge flows from a periphery to a center firm lacked significance.

Finally, because there was a nontrivial correlation (0.69) between two codified knowledge flows, I estimated models that included each codified knowledge flow separately. Models 2 and 3 indicated that the effects of two codified knowledge flows are not due to the collinearity between them. Each effect of codified knowledge flows was negative and significant. I also tested the same models after centering the variables of codified knowledge flows and their quadratic terms at their means. The results were robust.

5 Discussion and Conclusion

The purpose of this paper is to determine the effect of knowledge flows on the formation of interfirm cooperation. By distinguishing codified knowledge flow from tacit knowledge flow, I demonstrate that the antecedents of interfirm cooperation lie in codified knowledge flows. I find that intense codified knowledge flows weaken the formation of interfirm cooperation because codified knowledge flows offset the need for tacit knowledge flows. While uncertainty caused by distant technology components in codified knowledge flows hinders a center firm from pursuing interfirm cooperation, the uncertainty stimulates a periphery firm to pursue interfirm cooperation.

The findings of this paper contribute to the existing literature in four ways. First, by focusing on the effect of knowledge flows on interfirm cooperation, I complement the current understanding about the relations between the two variables: knowledge flows and interfirm cooperation. Drawing on well-established arguments that interfirm cooperation facilitates knowledge flows (Mowery, Oxley, and Silverman, 1996; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), I present evidence that interfirm cooperation could be endogenous to codified knowledge flows. That is, the results of this paper uphold the notion that knowledge flows can be not only the result but also cause of interfirm cooperation. Second, I relax the theoretical assumption of bidirectional and symmetric knowledge flows in literature, by addressing directional asymmetric codified knowledge flows separately. In examining those two-directional knowledge flows that have different impacts on the formation of interfirm cooperation, I refine the construct, technology distance in codified knowledge flows, which can characterize the asymmetry in technological uncertainty of the directional codified knowledge flows. Third, the conclusions formed during this study add an insight to our understanding of the role of uncertainty in forming interfirm cooperation. The literature provides contrasting explanations for the effects of uncertainty on interfirm cooperation (Williamson, 1991; Kogut and Zander, 1992). By examining the technological uncertainty caused by directional codified knowledge flows, I try to synthesize the positive or negative effects of uncertainty on the formation of interfirm cooperation within a knowledge network. Fourth, this study also contributes to extending the work on firms' technology and cooperation strategy by demonstrating that the technological changes such as adopting knowledge flows can be an antecedent to the formation of interfirm cooperation.

This study is not without limitations. First, I used the instance of interfirm cooperation as a proxy for tacit knowledge flows without distinguishing tacit knowledge flows from interfirm cooperation. However, I believe that this measure is a reasonable proxy for the tacit knowledge flows because if tacit knowledge flows between firms, there should be interfirm cooperation. Recall that it is not legitimate for individual engineers to communicate their tacit knowledge related to firm-owned technologies without the setting of interfirm cooperation. Also, interfirm cooperation in this paper most likely indicates tacit knowledge flows because I excluded any type of interfirm cooperation that may be not related to technology exchange or sharing. For example, I did not count instances of interfirm cooperation based on marketing or distribution alliances. Nevertheless, if possible, a separate proxy for tacit knowledge flows from interfirm cooperation might further solidify the results. Second, considerable unobserved factors may exist across firms in choosing technology strategies and thus intervene to form interfirm cooperation. To minimize this concern, I incorporate firm fixed-effects, environmental variables such as platform technology changes and industry consolidations, and periphery firms' age in the estimations. This approach may address the unobserved time-invariant heterogeneities across firms, the environmental changes, and firms' age dependent changes. Nevertheless, I acknowledge that due to the lack of data, the inability to fully address time-variant firm heterogeneity is clearly a limitation.

My findings imply that the impact of directional codified knowledge flows is absorbed in different ways and induces the formation of interfirm cooperation according to the firm's position in a knowledge network. The findings on the role of codified knowledge flows help explain a mechanism that guides firms when choosing their cooperating partners, presenting a possible answer to the question (Stuart, 1998): While a strong body of research has demonstrated that interfirm cooperation contributes to technology development and firm growth, why do some firms choose to cooperate and others do not? In the enterprise software industry, in which codified knowledge plays a central role in knowledge diffusion, my perspective implies that firms avoid the risk of interfirm cooperation by discerning preceding codified knowledge flows, and reduce the uncertainty of adopting distant technology components by manipulating interfirm cooperation. In particular, periphery firms may have the incentives to cooperate with a platform when the platform firm continuously introduces distant technological components that drive technological uncertainty in the knowledge network surrounding the platform.

Relatedly, this study has managerial implications for both platform and periphery firms seeking technologies that would not be codified. While platform firms encourage periphery firms to enter their platforms (Huang et al., 2013), my findings suggest that platform firms may first commit to attracting periphery firms that present proximate technologies so they can develop standard platforms among similar technologies. This implies that periphery firms with proximate technologies can wait for platforms to approach them, while periphery firms with distant technologies may access platforms first when they need tacit knowledge about platform technologies. Meanwhile, the platforms may need to pay attention to the composition of their platform-joining periphery firms and the technology boundary of their platforms. This is because the coverage of technologies on platform may determine the distance of technologies between platforms and periphery firms, which may affect periphery firms' choice of whether to collaborate. If platforms cover broad technology areas with a view to be a consolidated enterprise platform, platform firms should be proactive in obtaining cooperating periphery firms. On the contrary, if platforms focus on limited areas of technologies, they may attract periphery firms that possess distant technologies as first movers to form interfirm cooperation.

For future study, the finding that the patent stock of a periphery firm has a statistically significant negative effect on interfirm cooperation and that the patent stock of a center firm has a statistically significant positive effect may be an avenue for future research (Model 8 in Table 2). The impact of the patent stock of a center firm can be consistent with the literature that proposes that firms build entry barriers, fences, or preemptions by patenting (Cohen et al., 2000; Cockburn and McGarvie, 2011; Ceccagnoli, 2009) because a center firm can pursue interfirm cooperation as it secures the protection of its innovation by strong patent stock. On the contrary, the impact of the patent stock of a periphery firm raises the question: What is the role of patenting for periphery firms in a knowledge network? By accumulating patent stocks, a periphery firm may redirect its efforts toward building a new knowledge network that will position the periphery firm at the center rather than strengthening interfirm cooperation with a center firm in a focal knowledge network.

Finally, I conclude with remarks about the limitations of generalizing the results in this paper to extended contexts. Because this study is based on a single industry as well as a single knowledge network, future studies should test whether the results of this paper are replicable in other industries and multiple knowledge networks. I believe that the characterization of directional codified knowledge flows—asymmetries in intensity and technological uncertainty—should be generally applicable for future study.

6 References

Adler, P. 1996. The dynamic relationship between tacit and codified knowledge: Comments on Ikujiro Nonaka's "Managing Innovation as an organizational knowledge creation process. International Handbook of Technology Management, Amsterdam: North-Holland.

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. Administrative Science Quarterly, 45 (3): 425–455.

Ahuja, G., & Lampert, M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal, 22(6-7): 521-543

Alcacer, J., & Gittelman, M. 2004. Patent citations as a measure of knowledge flows: The influence of examiner citations. The Review of Economics and Statistics, 88(4): 774–779

Almeida, P., Song, J., & Grant, R.M. 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. Organization. Science, 13:147-161.

Bresnahan, T. F., & Greenstein, S. 1999. Technological competition and the structure of the computer industry. Journal of Industrial Economics, 47: 1–40.

Burkhardt, M. E., & Brass, D. J. 1990. Changing patterns or patterns of change: The effects of a change in technology on social network structure and power. Administrative Science Quarterly, 35: 104- 127.

Burt, R. S. 2004. Structural holes and good ideas. American Journal of Sociology, 110:349–99.

Cameron, A.C., & Trivedi, P.K. 2005. Microeconometrics: Methods and Applications , Cambridge. Cambridge University Press.

Cassiman, B., & Veugelers, R. 2002. R&D cooperation and spillovers: Some empirical evidence from Belgium. American Economic Review, 92: 1169–1184.

Ceccagnoli, M. 2009. Appropriability, preemption, and firm performance. Strategic Management Journal, 30(1): 81–98.

Ceccagnoli, M.,& Jiang, L. 2013. Licensing, cospecialized assets, and the buyer's productivity in developing external inventions. Strategic Management Journal, 34: 404–425

Chellappa, R. K., & Saraf, N. 2010. Alliances, rivalry and firm performance in enterprise systems software markets: A social network approach. Information Systems Research, 21(4): 849-871.

Cockburn, I. & MacGarvie, M. 2011. Entry and patenting in the software industry. Management Sci. 57(5):915–933.

Cohen, W., & Levinthal, D. 1989. Innovation and learning: The two faces of R&D. The Economic Journal, 99: 569–596.

Cohen, W., & Levinthal, D. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1): 128-152.

Cohen, W.M., Goto, A., Nagata, A., Nelson, R., & Walsh, J. 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. Research Policy, 31: 1349–1367.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent or not. NBER working paper no. 7552. Cambridge, MA: National Bureau of Economic Research.

Cohen, W.M., Walsh, J.P., 2000. R&D Spillovers, Appropriability and R&D Intensity: A Survey-Based Approach. Report to the Economic Assessment Office, NIST Advanced Technology Program.

Cowan, R., Jonard, N. & Zimmermann, J. B. (2007). Bilateral Collaboration and the Emergence of Innovation Networks. Management Science, 53(7): 1051–1067.

Dasgupta, P. & David, P., 1994. Towards a new economics of science. Research Policy, 23: 487–522.

Datamonitor, 2007. Global Application Software, Industry Profile. www.datamonitor.com (Accessed on September 20, 2010).

Davis, J., Eisenhardt, K., & Bingham, C. 2009. Complexity theory, market dynamism, and the strategy of simplerules. Administrative Science Quarterly,54: .413-452.

Dyer, J., & Nobeoka, K. 2000. Creating and managing a high performance knowledge-sharing network: The Toyota case. Strategic Management Journal, Special Issue, 21: 345–367.

Eisenhardt, K. M. & Martin,J. 2000. Dynamic capabilities: What are they? Strategic Management Journal, Special Issue, 21: 1105-1121.

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science, 47: 117–132.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. 2006. Do alliances promote knowledge flows? Journal of Financial Economics, 80(1): 5–33.

Griliches Z (Ed.). 1984. R & D, patents, and productivity. University of Chicago Press: Chicago

Grimaldi, R., & Torrisi, S. 2001. Codified-tacit and general-specific knowledge in the division of labour among firms. A study of the software industry. Research Policy 30(9): 1425-1442.

Gulati R. 1998. Alliances and networks. Strategic Management Journal, Special Issue, 19: 293–317.

Huang, P., Ceccagnoli, M., Forman, C., & Wu, D. 2013. Appropriability Mechanisms and the Platform Partnership Decision: Evidence from Enterprise Software, 59(1): 101-121.

Jaffe, A. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. American Economic Review, 76: 984–1001.

Jiang, L., Tan, J., & Thursby, M. C. 2009. Incumbent invention in emerging fields: Evidence from the semiconductor industry. Strategic Management Journal, Forthcoming.

Knott, A. M., Posen, H., & Wu, B. 2009. Spillover asymmetry and why it matters. Management Science, 55(3): 373–388.

Kogut, B. 1988. Joint ventures: Theoretical and emperical perspectives. Strategic Management Journal, 9(4): 319–332.

Kogut, B. & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science, 3(3): 383-397.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. Strategic Management Journal, Summer Special Issue, 13: 111-125.

Makadok, R. & Coff, R. 2009. Both Market and Hierarchy: An Incentive-System Theory of Hybrid Governance Forms. Academy of Management Review, 34(2): 297-319.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, Winter Special Issue, 17: 77–92.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1998. Technological overlap and interfirm cooperation: Implications for the resource-based view of the firm. Research Policy, 27: 507–523.

Nelson, R., & Winter, S. 1982. An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Nonaka, I. 1994. A dynamic theory of organizational knowledge creation. Organizational Science, 5(1): 14-37.

Owen-Smith, J., & Powell,W. 2004. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. Organization Science, 15: 5–21.

Polanyi, M., 1966, The Tacit Dimension. Routledge & Kegan Paul, London.

Roach, M, Cohen, W. 2012. Lens or Prism? A Comparative Assessment of Patent Citations as a Measure of Knowledge Flows from Public Research. Management Science, forthcoming

Rosenkopf, L., Metiu, A., & George, V. 2001. From the bottom up? Technical committee activity and alliance formation. Administrative Science Quarterly, 46:748-772.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. Management Science, 49(6): 751–766.

Rothaermel, F.T., & W. Boeker. 2008. Old technology meets new technology: complementarities, similarities, and alliance formation. Strategic Management Journal, 29(1): 47-77.

Sorenson, O., J., Rivkin, W., & Fleming, L. 2006. Complexity, networks and knowledge flow. Research Policy, 35(7): 994-1017

Spear, S., & Bowen, K. 1999. Decoding the DNA of the Toyota production system. Harvard Business Review. (Sept./Oct.): 97–106.

Spence, A. 1984. Cost reduction, competition, and industry performance. Econometrica, 52: 101–121.

Stuart, T. E. 1998. Network positions and propensities to collaborate: An investigation of strategic alliance formulation in a high-technology industry. Administrative Science Quarterly, 43: 668–698.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, cooperation, licensing and public policy. Research Policy, 15: 285–305.

Tushman, M., & Anderson, P. 1986. Technological Discontinuities and Organizational Environments, Administrative Science Quarterly, 31: 439-465.

Uzzi, B.1997. Social structure and competition in interfirm networks: The paradox of embeddedness. Administrative Science Quarterly, 42: 36–67.

Van de Ven, A., Delbecq, A., and Koenig, J. 1976. Determinants of coordination modes within organizations. American Sociological Review, 41: 322-338

Von Hippel, E. 1988. The Sources of Innovation. New York: Oxford University Press.

Von Hippel, E. 1994. “Sticky information” and the locus of problem solving: Implications for innovation. Management Science, 40(4): 429–439.

Williamson, O. E. 1991. Comparative economic organization: the analysis of discrete structural alternatives. Administrative Science Quarterly, 36: 269-296.

Williamson, O. E. 1993. Transaction cost economics and organization theory. Industrial and Corporate Change, 2: 107-56.

Woodridge, J. 2002. Econometric Analysis of Cross Section and Panel Data, Cambridge, MA: MIT Press.

Zander, U., & Kogut, B. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. Organization Science, 6(1): 7–92.

Zollo, M., & Winter, S. G. 2002. Deliberate learning and the evolution of dynamic capabilities. Organization Science, 13: 339-351.

Table 3.1 Summary Statistics

	Variable	1	2	3	4	5	6	7	8
1	Formation of interfirm cooperation								
2	Codified knowledge flows from a periphery to a center firm	0.003							
3	Codified knowledge flows from a center to a periphery firm	-0.005	0.690						
4	Technology distance from a periphery to a center firm	0.062	-0.154	-0.123					
5	Technology distance from a center to a periphery firm	0.072	-0.064	-0.207	-0.079				
6	Prior interfirm cooperation	0.228	0.169	0.178	-0.032	0.039			
7	Firm age	0.099	0.291	0.215	-0.014	0.029	0.230		
8	Acquisition	-0.100	-0.047	-0.108	-0.024	0.077	-0.062	-0.119	
9	Platform technology shift	0.045	-0.020	-0.048	0.025	-0.033	0.028	-0.007	0.045
10	Bidirectional knowledge flows	0.022	0.341	0.477	-0.218	-0.345	0.179	0.190	-0.122
11	Patent stock of a periphery firm	0.070	-0.048	-0.057	0.103	0.101	0.130	0.108	0.000
12	Patent stock of a center firm	-0.074	-0.108	-0.234	-0.063	0.326	-0.227	-0.220	0.092
13	Industry consolidation	-0.021	0.070	0.029	0.069	0.017	0.012	0.002	0.028
	N	1110	1110	1110	1110	1110	1110	1110	1110
	N-g	243	243	243	243	243	243	243	243
	Mean	0.158	7.45	3.3171	0.809	0.855	0.558	24.77	0.105
	Std. Dev.	0.422	24.55	9.4582	0.272	0.237	1.074	33.44	0.306
	Min	0	0	0	0	0	0	0	0
	Max	4	310	81	1	1	7	178	1

All correlation coefficients above 0.07 are significant at p<0.05.

		9	10	11	12	13
10	Bidirectional knowledge flows	-0.052				
11	Patent stock of a periphery firm	0.091	-0.093			
12	Patent stock of a center firm	-0.058	-0.404	-0.127		
13	Industry consolidation	0.511	0.045	-0.054	0.044	
	N	1110	1110	1110	1110	1110
	N-g	243	243	243	243	243
	Mean	0.230	0.249	25.64	681.55	0.096
	Std. Dev.	0.421	0.432	154.04	897.04	0.295
	Min	0	0	0	0	0
	Max	1	1	987.383	2185.92	1

All correlation coefficients above 0.07 are significant at p<0.05.

Table 3.2 Fixed Effects Poisson Regression Results

	D.V: Formation of Interfirm Cooperation Estimated Coefficients in top line (Robust S.E in parentheses) [Incidence rate ratios in bracket]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.009*		-0.006	-0.023**	-0.008	-0.021*	-0.005
		(0.0048)		(0.0076)	(0.0111)	(0.0087)	(0.0114)	(0.0062)
		[0.991]		[0.994]	[0.977]	[0.932]	[0.979]	[0.995]
Codified knowledge flows from a center to a periphery firm			-0.027**	-0.017	-0.019	-0.071***	-0.058*	-0.026
			(0.0106)	(0.0177)	(0.0165)	(0.0260)	(0.0302)	(0.0199)
			[0.973]	[0.983]	[0.981]	[0.992]	[0.944]	[0.975]
Technology distance from a periphery to a center firm								-1.080*
								(0.6008)
								[0.340]
Technology distance from a center to a periphery firm								2.265***
								(0.7943)
								[9.635]
Codified knowledge flows from a periphery to a center firm ^2					7E-05**		6E-05*	
					(3E-05)		(3E-05)	
					[1.0001]		[1.0001]	
Codified knowledge flows from a center to a periphery firm^2						0.001*	0.001	
						(0.0006)	(0.0006)	
						[1.001]	[1.001]	
Zero Codified knowledge flows from a periphery to a center firm								1.374***
								(0.4259)
Zero Codified knowledge flows from a center to a periphery firm								0.455
								(0.4026)
Prior interfirm cooperation	-0.088*	-0.118***	-0.103	-0.114**	-0.123**	-0.119**	-0.125**	-0.048
	(0.0463)	(0.0407)	(0.0672)	(0.0494)	(0.0495)	(0.0495)	(0.0505)	(0.0639)
Firm age	0.144	0.132	0.137	0.132	0.142	0.136	0.142	0.102
	(0.1082)	(0.1081)	(0.1050)	(0.1059)	(0.1067)	(0.1037)	(0.1042)	(0.0987)
Acquisition	-0.871	-1.024	-1.084	-1.099	-1.156*	-1.239*	-1.244*	-1.609***
	(0.6121)	(0.6646)	(0.6623)	(0.6754)	(0.6986)	(0.6683)	(0.6880)	(0.5983)

(continued)

Table 3.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Platform technology shift	0.556**	0.486*	0.466*	0.453*	0.416	0.406	0.390	0.427*
	(0.2605)	(0.2570)	(0.2700)	(0.2650)	(0.2681)	(0.2644)	(0.2661)	(0.2360)
Bidirectional knowledge flows	0.261	0.377	0.392	0.422	0.580	0.610	0.675*	1.439***
	(0.3829)	(0.3976)	(0.3737)	(0.3940)	(0.3819)	(0.3841)	(0.3720)	(0.5465)
Patent stock of a periphery firm	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002**
	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0009)	(0.0008)
Patent stock of a center firm	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Industry consolidation	-0.556	-0.506	-0.493	-0.482	-0.458	-0.441	-0.440	-0.627*
	(0.3785)	(0.3654)	(0.3848)	(0.3754)	(0.3759)	(0.3688)	(0.3688)	(0.3512)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-252.412	-250.227	-250.068	-249.583	-247.906	-247.880	-247.031	-234.301
N	658	658	658	658	658	658	658	658
N-g	67	67	67	67	67	67	67	67

* p<0.10 ** p<0.05 *** p<0.01

Notes. Robust standard errors clustered by each firm are in parentheses. Incident rate ratios [IRR] are in brackets.

Table 3.3 Fixed Effects Logit Regression Results

	D.V: Formation of Interfirm Cooperation (binary)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.010		-0.007	-0.034**	-0.010	-0.032**	-0.010
		(0.0062)		(0.0073)	(0.0157)	(0.0080)	(0.0160)	(0.0074)
Codified knowledge flows from a center to a periphery firm			-0.026	-0.014	-0.014	-0.077*	-0.057	-0.031
			(0.0170)	(0.0204)	(0.0211)	(0.0452)	(0.0458)	(0.0225)
Technology distance from a periphery to a center firm								-2.147***
								(0.8065)
Technology distance from a center to a periphery firm								2.691***
								(0.9738)
Codified knowledge flows from a periphery to a center firm ^2					1E-04**		8E-05*	
					(0.0001)		(0.0001)	
Codified knowledge flows from a center to a periphery firm^2						0.001	0.001	
						(0.0007)	(0.0007)	
Zero Codified knowledge flows from a periphery to a center firm								2.799***
								(0.6542)
Zero Codified knowledge flows from a center to a periphery firm								1.130
								(0.7144)
Prior interfirm cooperation	-0.117	-0.168	-0.141	-0.166	-0.191*	-0.175*	-0.193*	-0.140
	(0.0974)	(0.1030)	(0.1004)	(0.1033)	(0.1057)	(0.1040)	(0.1057)	(0.1147)
Firm age	0.216	0.218	0.220	0.219	0.231	0.223	0.230	0.237
	(0.1572)	(0.1587)	(0.1583)	(0.1589)	(0.1601)	(0.1591)	(0.1600)	(0.1661)

(continued)

Table 3.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Acquisition	-0.594	-0.731	-0.771	-0.786	-0.845	-0.935	-0.934	-1.155
	(0.7761)	(0.7829)	(0.7882)	(0.7887)	(0.7933)	(0.7991)	(0.8005)	(0.8925)
Platform technology shift	0.795**	0.761*	0.735*	0.739*	0.716*	0.698*	0.690*	0.821*
	(0.3945)	(0.3977)	(0.3973)	(0.3988)	(0.4004)	(0.4004)	(0.4015)	(0.4271)
Bidirectional knowledge flows	0.444	0.544	0.565	0.581	0.778*	0.772*	0.879**	2.550***
	(0.4095)	(0.4144)	(0.4159)	(0.4174)	(0.4298)	(0.4347)	(0.4393)	(0.7251)
Patent stock of a periphery firm	2E-04	-3E-04	-2E-04	-4E-04	-0.001	-2E-04	-0.001	-0.001
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0013)	(0.0013)
Patent stock of a center firm	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Industry consolidation	-0.473	-0.454	-0.436	-0.439	-0.438	-0.399	-0.421	-0.601
	(0.5038)	(0.5072)	(0.5062)	(0.5074)	(0.5072)	(0.5075)	(0.5073)	(0.5472)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-189.490	-187.886	-188.181	-187.649	-185.650	-186.400	-185.070	-168.050
N	658	658	658	658	658	658	658	658
N-g	67	67	67	67	67	67	67	67

* p<0.10 ** p<0.05 *** p<0.01

Notes. Classical standard errors (independent and identically distributed) are in parentheses.

Table 3.4 Fixed Effects OLS Results

	D.V: Formation of Interfirm Cooperation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.003***		-0.003*	-0.008**	-0.003**	-0.007**	-0.003**
		(0.0012)		(0.0015)	(0.0037)	(0.0015)	(0.0035)	(0.0015)
Codified knowledge flows from a center to a periphery firm			-0.008***	-0.003	-0.003	-0.014**	-0.011*	-0.004
			(0.0022)	(0.0023)	(0.0024)	(0.0067)	(0.0066)	(0.0026)
Technology distance from a periphery to a center firm								-0.136
								(0.0860)
Technology distance from a center to a periphery firm								0.318***
								(0.1179)
Codified knowledge flows from a periphery to a center firm ^2					1E-05*		2E-05	
					(1E-05)		(1E-05)	
Codified knowledge flows from a center to a periphery firm^2						1E-04	1E-04	
						(0.0001)	(0.0001)	
Zero Codified knowledge flows from a periphery to a center firm								0.359***
								(0.0972)
Zero Codified knowledge flows from a center to a periphery firm								0.177*
								(0.0943)
Prior interfirm cooperation	-0.056**	-0.069***	-0.060**	-0.068***	-0.070***	-0.069***	-0.070***	-0.063***
	(0.0230)	(0.0242)	(0.0250)	(0.0244)	(0.0253)	(0.0244)	(0.0252)	(0.0240)
Firm age	0.014	0.016	0.016	0.016	0.018	0.016	0.018	0.024
	(0.0169)	(0.0167)	(0.0168)	(0.0167)	(0.0166)	(0.0166)	(0.0165)	(0.0165)

(continued)

Table 3.4 Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Acquisition	-0.036	-0.075	-0.078	-0.087	-0.098	-0.106	-0.111	-0.114*
	(0.0691)	(0.0698)	(0.0722)	(0.0721)	(0.0725)	(0.0725)	(0.0724)	(0.0595)
Platform technology shift	0.096	0.088	0.083	0.084	0.080	0.076	0.075	0.088
	(0.0659)	(0.0642)	(0.0643)	(0.0644)	(0.0631)	(0.0627)	(0.0622)	(0.0597)
Bidirectional knowledge flows	0.003	0.037	0.046	0.049	0.075	0.081	0.095	0.364***
	(0.0715)	(0.0661)	(0.0668)	(0.0673)	(0.0629)	(0.0646)	(0.0638)	(0.0932)
Patent stock of a periphery firm	-9E-05	-3E-04	-2E-04	-3E-04	-3E-04	-3E-04	3E-04	-4E-04
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Patent stock of a center firm	1E-04***	2E-04***	2E-04***	2E-04***	2E-04***	2E-04***	2E-04***	1E-04***
	(4E-05)	(4E-05)	(0.0001)	(4E-05)	(4E-05)	(0.0001)	(5E-05)	(0.0001)
Industry consolidation	-0.100	-0.090	-0.091	-0.088	-0.085	-0.081	-0.080	-0.090
	(0.0859)	(0.0844)	(0.0848)	(0.0844)	(0.0837)	(0.0826)	(0.0826)	(0.0802)
Constant	-0.091	-0.283	-0.195	-0.292	-0.325	-0.304	-0.328	-0.875***
	(0.2051)	(0.2446)	(0.2084)	(0.2384)	(0.2319)	(0.2367)	(0.2324)	(0.2896)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.099	0.121	0.113	0.123	0.130	0.128	0.133	0.172
N	1110	1110	1110	1110	1110	1110	1110	1110
N-g	243	243	243	243	243	243	243	243

* p<0.10 ** p<0.05 *** p<0.01

Notes. Robust standard errors clustered by each firm are in parentheses.

Table 3.5 Fixed Effects Poisson Regression Results: Robustness Check with Year Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.009		-0.006	-0.024*	-0.008	-0.022*	-0.005
		(0.0054)		(0.0078)	(0.0128)	(0.0084)	(0.0130)	(0.0064)
Codified knowledge flows from a center to a periphery firm			-0.028**	-0.017	-0.019	-0.074***	-0.061**	-0.026
			(0.0117)	(0.0182)	(0.0171)	(0.0217)	(0.0245)	(0.0223)
Technology distance from a periphery to a center firm								-1.119*
								(0.6063)
Technology distance from a center to a periphery firm								2.304***
								(0.8768)
Codified knowledge flows from a periphery to a center firm ^2					0.0001**		0.0001	
					(0.00004)		(0.00003)	
Codified knowledge flows from a center to a periphery firm^2						0.001**	0.001*	
						(0.0005)	(0.0005)	
Zero Codified knowledge flows from a periphery to a center firm								1.343***
								(0.4416)
Zero Codified knowledge flows from a center to a periphery firm								0.227
								(0.4759)
Prior interfirm cooperation	-0.064	-0.094**	-0.075	-0.087	-0.095*	-0.090	-0.096*	-0.032
	(0.0535)	(0.0468)	(0.0709)	(0.0536)	(0.0533)	(0.0557)	(0.0554)	(0.0676)
Firm age	-0.095*	-0.077	-0.076	-0.072	-0.058	-0.056	-0.050	-0.042
	(0.0524)	(0.0492)	(0.0586)	(0.0532)	(0.0514)	(0.0504)	(0.0497)	(0.0488)

(continued)

Table 3.5 Continued

Acquisition	-1.009*	-1.127*	-1.186*	-1.191*	-1.234*	-1.317**	-1.318**	-1.499***
	(0.6126)	(0.6459)	(0.6492)	(0.6577)	(0.6708)	(0.6420)	(0.6556)	(0.5740)
Bidirectional knowledge flows	0.157	0.283	0.325	0.348	0.519	0.563	0.628	1.272**
	(0.4024)	(0.4444)	(0.4093)	(0.4391)	(0.4396)	(0.4193)	(0.4240)	(0.5533)
Patent stock of a periphery firm	-0.001*	-0.002**	-0.002**	-0.002**	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0008)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0004)
Patent stock of a center firm	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-247.333	-245.120	-245.026	-244.514	-242.754	-242.506	-241.696	-230.318
N	658	658	658	658	658	658	658	658
N-g	67	67	67	67	67	67	67	67

* p<0.10 ** p<0.05 *** p<0.01

Notes. Robust standard errors clustered by each firm are in parentheses. The years of platform technology shift and industry consolidation are omitted as a baseline to obtain convergence.

Table 3.6 Fixed Effects Logit Regression Results: Robustness Check with Year Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.011*		-0.009	-0.036**	-0.012	-0.033**	-0.010
		(0.0060)		(0.0071)	(0.0158)	(0.0076)	(0.0163)	(0.0070)
Codified knowledge flows from a center to a periphery firm			-0.035**	-0.010	-0.010	-0.077*	-0.057	-0.028
			(0.0169)	(0.0205)	(0.0214)	(0.0457)	(0.0469)	(0.0225)
Technology distance from a periphery to a center firm								-2.503***
								(0.8027)
Technology distance from a center to a periphery firm								2.613***
								(0.9702)
Codified knowledge flows from a periphery to a center firm ^2					0.000*		0.0001	
					(0.0000)		(0.0001)	
Codified knowledge flows from a center to a periphery firm^2						0.001	0.001	
						(0.0006)	(0.0007)	
Zero Codified knowledge flows from a periphery to a center firm								2.741***
								(0.6411)
Zero Codified knowledge flows from a center to a periphery firm								0.835
								(0.6809)
Prior interfirm cooperation	-0.117	-0.183*	-0.142	-0.182*	-0.208*	-0.189*	-0.207*	-0.097
	(0.0980)	(0.1038)	(0.0972)	(0.1039)	(0.1061)	(0.1044)	(0.1061)	(0.1116)
Firm age	-0.103**	-0.076	-0.039	-0.073	-0.054	-0.054	-0.045	-0.004
	(0.0527)	(0.0537)	(0.0453)	(0.0543)	(0.0551)	(0.0552)	(0.0555)	(0.0602)

(continued)

Table 3.6 Continued

Acquisition	-0.972	-1.127	-1.396*	-1.164	-1.224	-1.305*	-1.310*	-1.512*
	(0.7692)	(0.7793)	(0.7741)	(0.7839)	(0.7899)	(0.7908)	(0.7944)	(0.8647)
Bidirectional knowledge flows	0.193	0.319	0.158	0.340	0.535	0.530	0.630	2.081***
	(0.4095)	(0.4147)	(0.3985)	(0.4161)	(0.4294)	(0.4313)	(0.4364)	(0.7006)
Patent stock of a periphery firm	-0.001	-0.002	-0.001	-0.002	-0.002*	-0.002	-0.002*	-0.003**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Patent stock of a center firm	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-184.649	-182.422	-192.351	-182.311	-180.448	-180.908	-179.797	-163.697
N	658	658	658	658	658	658	658	658
N-g	67	67	67	67	67	67	67	67

* p<0.10 ** p<0.05 *** p<0.01

Notes. Classical standard errors (independent and identically distributed) are in parentheses. The years of platform technology shift and industry consolidation are omitted as a baseline to obtain convergence.

Table 3.7 Fixed Effects OLS Regression Results: Robustness Check with Year Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Codified knowledge flows from a periphery to a center firm		-0.003*** (0.0012)		-0.003* (0.0016)	-0.008** (0.0033)	-0.003** (0.0016)	-0.007** (0.0031)	-0.003** (0.0015)
Codified knowledge flows from a center to a periphery firm			-0.009*** (0.0023)	-0.003 (0.0023)	-0.002 (0.0023)	-0.015** (0.0064)	-0.012* (0.0061)	-0.004 (0.0026)
Technology distance from a periphery to a center firm								-0.136 (0.0934)
Technology distance from a center to a periphery firm								0.308*** (0.1184)
Codified knowledge flows from a periphery to a center firm ^2					0.00002** (0.00001)		0.00002* (0.00001)	
Codified knowledge flows from a center to a periphery firm^2						0.0002* (0.0001)	0.0002 (0.0001)	
Zero Codified knowledge flows from a periphery to a center firm								0.332*** (0.1059)
Zero Codified knowledge flows from a center to a periphery firm								0.148 (0.1051)
Prior interfirm cooperation	-0.053** (0.0251)	-0.066*** (0.0241)	-0.058** (0.0251)	-0.065*** (0.0243)	-0.067*** (0.0247)	-0.065*** (0.0244)	-0.067*** (0.0247)	-0.059** (0.0236)
Firm age	-0.024** (0.0110)	-0.019* (0.0105)	-0.012 (0.0084)	-0.018* (0.0106)	-0.015 (0.0101)	-0.016 (0.0103)	-0.014 (0.0100)	-0.007 (0.0118)

(continued)

Table 3.7 Continued

Acquisition	-0.062	-0.098	-0.132*	-0.109	-0.120	-0.128*	-0.133*	-0.124**
	(0.0686)	(0.0696)	(0.0729)	(0.0729)	(0.0733)	(0.0731)	(0.0732)	(0.0613)
Bidirectional knowledge flows	-0.013	0.021	0.015	0.032	0.060	0.067	0.081	0.319***
	(0.0713)	(0.0692)	(0.0702)	(0.0689)	(0.0658)	(0.0654)	(0.0657)	(0.0973)
Patent stock of a periphery firm	-0.0002*	-0.0004**	-0.0003**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Patent stock of a center firm	0.0002***	0.0002***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00005)	(0.00005)	(0.0001)	(0.00005)	(0.0001)	(0.0001)	(0.00005)	(0.0001)
Constant	0.671**	0.573**	0.440**	0.558**	0.493*	0.524**	0.478*	0.084
	(0.2805)	(0.2664)	(0.2215)	(0.2690)	(0.2569)	(0.2630)	(0.2553)	(0.3388)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.124	0.145	0.110	0.147	0.155	0.153	0.158	0.189
N	1110	1110	1110	1110	1110	1110	1110	1110
N-g	243	243	243	243	243	243	243	243

* p<0.10 ** p<0.05 *** p<0.01

Notes. Robust standard errors clustered by each firm are in parentheses. The years of platform technology shift and industry consolidation are omitted as a baseline to obtain convergence.

Table 3.8 Fixed Effects Poisson Regression Results with Novelty/ Post-legal regime change

	(1)	(2)	(3)
Novelty from a periphery to a center firm	-0.017***	-0.019***	
	(0.0031)	(0.0033)	
Novelty from a center to a periphery firm	0.003	0.008	
	(0.0081)	(0.0063)	
Codified knowledge flows from a periphery to a center firm	0.017***	0.019***	
	(0.0059)	(0.0056)	
Codified knowledge flows from a center to a periphery firm	-0.048**	-0.065***	
	(0.0228)	(0.0249)	
Technology distance from a periphery to a center firm		-0.821	
		(0.6335)	
Technology distance from a center to a periphery firm		2.574***	
		(0.7014)	
Zero Codified knowledge flows from a periphery to a center firm		1.289***	
		(0.4091)	
Zero Codified knowledge flows from a center to a periphery firm		0.297	
		(0.3753)	
Post-legal regime change			-1.086***
			(0.404)
Prior interfirm cooperation	-0.107**	-0.048	-0.071
	(0.0436)	(0.0628)	(0.0492)
Firm age	0.118	0.087	0.161
	(0.1080)	(0.1025)	(0.1111)
Acquisition	-1.194*	-1.707***	-0.821
	(0.6768)	(0.6140)	(0.5951)
Platform technology shift	0.416	0.358	0.218
	(0.2757)	(0.2440)	(0.3042)
Bidirectional knowledge flows	0.608*	1.587***	0.245
	(0.3378)	(0.4786)	(0.3878)
Patent stock of a periphery firm	-0.001	-0.002***	-0.001
	(0.0009)	(0.0007)	(0.001)
Patent stock of a center firm	0.001***	0.001***	0.001***
	(0.0003)	(0.0002)	(0.0003)
Industry consolidation	-0.502	-0.629*	-0.358
	(0.4002)	(0.3602)	(0.3733)
Year Effect	Yes	Yes	Yes
Log-likelihood	-244.974	-229.501	-249.996
N	658	658	658
N-g	67	67	67

* p<0.10 ** p<0.05 *** p<0.01

Notes. Robust standard errors clustered by each firm are in parentheses.

CHAPTER 3 APPENDIX

Comparative Statics Analysis

I present a comparative statics analysis to formalize the effect of codified knowledge flows on the utility of interfirm cooperation. Consider a utility of interfirm cooperation, U, that is determined by a benefit of tacit knowledge, B, and transaction cost, C. The utilities of interfirm cooperation of a center firm (denoted by c) and a periphery firm (denoted by p) are, respectively:

$$U^c = B^c - C^c,$$

$$U^p = B^p - C^p.$$

The effect of the intensity of two directional codified knowledge flows, K^c(knowledge flows from a periphery firm to a center firm) and K^p(knowledge flows from a center firm to a periphery firm) on the utility of interfirm cooperation can be analyzed from the first order condition, $\frac{\partial U^c}{\partial K^c}$ and $\frac{\partial U^p}{\partial K^p}$. For both a center firm and a periphery firm, because codified knowledge flows offset the need for tacit knowledge and reduce the benefit of tacit knowledge, $\frac{\partial B^c}{\partial K^c} < 0$ and $\frac{\partial B^p}{\partial K^p} < 0$. Because disclosed knowledge in codified knowledge flows increases the expropriation risk, $\frac{\partial C^c}{\partial K^c} > 0$ and $\frac{\partial C^p}{\partial K^p} > 0$. Hence, I propose that:

$$\frac{\partial U^c}{\partial K^c} = \underbrace{\frac{\partial B^c}{\partial K^c}}_{-} - \underbrace{\frac{\partial C^c}{\partial K^c}}_{-} < 0\ ; \qquad (1)$$

$$\frac{\partial U^p}{\partial K^p} = \underbrace{\frac{\partial B^p}{\partial K^p}}_{-} - \underbrace{\frac{\partial C^p}{\partial K^p}}_{-} < 0\ . \qquad (2)$$

The effect of uncertainty in two directional codified knowledge flows, u^c in K^c, and u^p in K^p, on the utility of interfirm cooperation can be analyzed from the first order condition, $\frac{\partial U^c}{\partial u^c}$ and $\frac{\partial U^p}{\partial u^p}$. From the perspective of a center firm, because uncertain technological components of a periphery firm have a risk of obsolescence, increasing u^c does not affect the need for tacit knowledge, and thus, $\frac{\partial B^c}{\partial u^c} = 0$, because the governance cost for a bilateral relationship in interfirm cooperation increases under uncertainty, $\frac{\partial C^c}{\partial u^c} > 0$. From the perspective of a periphery firm, because tacit knowledge from a center firm is beneficial for understanding uncertain components introduced by a center firm, $\frac{\partial B^p}{\partial u^p} > 0$; because expropriation risk by a center firm is low in cooperation for an uncertain distant technology, $\frac{\partial C^p}{\partial u^p} < 0$. Hence, I propose that:

$$\frac{\partial U^c}{\partial u^c} = \underbrace{\frac{\partial B^c}{\partial u^c}}_{0} - \underbrace{\frac{\partial C^c}{\partial u^c}}_{-} < 0\ ; \qquad (3)$$

$$\frac{\partial U^p}{\partial u^p} = \underbrace{\frac{\partial B^p}{\partial u^p}}_{+} - \underbrace{\frac{\partial C^p}{\partial u^p}}_{+} > 0\ . \qquad (4)$$

The propositions formulate the four testable hypotheses in the main section of this paper.

CHAPTER 4

THE IMPACTS OF COMMERCIALIZATION-ORIENTED SCIENCE AND TECHNOLOGY PROGRAMS ON UNIVERSITY RESEARCH: EVIDENCE FROM THE U.S. NATIONAL NANOTECHNOLOGY INITIATIVE

1 Introduction

Since Vannevar Bush's (1945) influential report, *Science: The Endless Frontier*, that highlighted the importance of basic research for advances in applied research and commercialization, university research has become a major vehicle through which governments seek to promote national economic growth. Based on the logic that stronger government support would enhance the effectiveness of the national innovation system, government science and technology (S&T) programs have become primary funding sources of university research in the U.S. (Nelson, 2004; Stephan, 2010). These programs are often associated with specific missions to be accomplished, as famously represented in the Apollo Program that aimed at "landing a man on the Moon."[34] In fact, over 90% of the government research and development (R&D) spending in the U.S. is considered to have mission-oriented rationales (Mowery, 2009). How might, then, targeted government S&T programs have influenced the nature of research in the U.S. universities, arguably

[34] On May 25, 1961, addressing to a joint session of the U.S. Congress, then President John F. Kennedy stated a goal of "landing a man on the Moon and returning him safely to the Earth" by the end of the 1960s. This led to the Apollo Program, by far the largest single government S&T program in the U.S. history.

the most significant beneficiary of such programs? This paper is our attempt to examine this question.

While national priorities play a role in setting broad research directions in Bush's manifesto, his original argument suggested a high degree of autonomy for science (Bush, 1945; Nelson, 2004; Mowery, 2009). Further, researchers have argued that decisions on specific areas to be funded should be left to scientists (Martin, 2003; Mowery, 2009). This casts a fundamental contrast with government S&T programs that promote mission-oriented initiatives, which may redirect university research to work on specific technology areas to maximize economic payoffs from the funding (Dasgupta and David, 1994). In particular, government-mandated missions such as ensuring the U.S. economic leadership may significantly affect the institutions of knowledge production and, hence, alter the landscape and flows of knowledge. It is generally understood that universities specialize in basic research (Nelson, 1959; Dasgupta and David, 1994), advance technology developments by often bringing about serendipitous exploration and technological breakthroughs (Mansfield, 1991; Nelson, 2004), and operate on a functional norm that substantive findings should be universally available to the research community (Merton, 1973). Government S&T programs with specific orientations such as commercialization can undermine these general assumptions on university research. We posit that commercialization-oriented S&T programs alter the characteristics of university research in technology development by influencing the direction of university research and by potentially overemphasizing the link to commercialization.

Despite the existing research on the influence of government funding on overall research outcomes, little is known about how government initiatives with specific targets may interfere with science and technology (Jaffe, 2006). Researchers have recently begun to address this issue by investigating the role of institutions and science policy in knowledge accumulation and the direction of scientific research (Murray et al., 2009; Furman, Murray, and Stern, 2010; Furman and Stern, 2010). Among what remains underexplored is the effect of government initiatives on knowledge flows and the nature of knowledge produced in the institutions such as universities that rely heavily on government funding. This omission is puzzling because government initiatives may be conflicting with the propositions that institutions of scientific research should be self-governed and thus independently decide the priority of their research agenda (Polanyi, 1962), and that the results of scientific research should be publicly disclosed and shared (Dasgupta and David, 1994; Nelson, 2004). To fill this void, we examine the impacts of a particular S&T program on university research in terms of the direction of knowledge flow between the university and the industry and the characteristics of research output such as branching-out to novel technologies, research scope and technological breakthroughs.

We argue that this program's particular emphasis on commercialization will induce university research to increasingly utilize knowledge flows from industry because firms tend to have technologies to solve problems that are directly relevant to market demand; due to greater interests in economic returns, university researchers will reduce accessibility to their findings through secrecy and incomplete disclosures, which, in turn, forecloses their own possibility of branching-out to subsequent novel technologies. We also contend that a focused research direction mandated by the program will influence university research to reduce the exploration of uncertain technologies and hence the variance of technological outcomes, and thereby lead to curtailed technological breakthroughs.

Our empirical setting is the National Nanotechnology Initiative (NNI), a U.S. federal government S&T program launched in 2000. Since its inception, the NNI has coordinated the disbursement of over $14 billion by 2011. By funneling the budget into nanotechnology R&D, the NNI guides the direction of university research toward the research agenda it has set up (Bush, 1945; Dasgupta and David, 1994; Mowery, 2009). The NNI is clearly a targeted government initiative in that it not only serves general government missions in national defense, agriculture, health and education, but also pursues its own mission of securing the economic leadership of the U.S. in nanotechnology.[35] In particular, the NNI is intended to "advance the U.S. productivity and industrial competitiveness through coordinated investments in nanotechnology."[36] Based on this mandate, we characterize the NNI as the onset of a policy intervention that emphasizes the commercialization of nanotechnology and a focused research direction to attain national economic growth. This program sets the university apart from the private sector that was largely unaffected by this policy drive. It also distinguishes the U.S. from other countries that were free of such a policy shift during the period of our study. Hence, the NNI provides a nice natural experiment that we can exploit to isolate the impact of this particular policy intervention on university research outcomes.

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[35] The President's Committee of Advisors on Science and Technology noted that the NNI has an "excellent multi-agency framework to ensure U.S. leadership in this emerging field that will be essential for economic and national security leadership in the first half of the next century" (NNI, *The Initiative and Its Implementation Plan*, 2000).
[36] *The 21st Century Nanotechnology Research and Development Act*. Public Law 108-153. The 108th Congress.

Analyzing 3,720 nanotechnology patents filed with the United States Patent and Trademark Office (USPTO) between 1996 and 2007, we find support for our hypotheses. Specifically, our difference-in-differences estimation show that, following the NNI, U.S. universities have become 1) more reliant on industry-generated knowledge; 2) less prone to branch out to novel technology areas; 3) narrower in patent scopes; and 4) less likely to produce technological breakthroughs. These outcomes are totally counterintuitive because the goals of government S&T programs are in general to facilitate knowledge transfers from university to industry, not the reverse, and to build a strong national innovation system characterized by greater innovative output. Our findings suggest that targeted S&T policy interventions do exert significant impacts on university research, but potentially in an unexpected way.

2 NNI as A Natural Experiment

The NNI is the U.S. federal interagency program for coordinating R&D and enhancing communication and collaborative activities in nanoscale science, engineering and technology. The NNI represents the individual and cooperative nanotechnology-related activities of 25 federal agencies[37] with a range of research and regulatory roles

[37] The federal agencies participating in the NNI include Consumer Product Safety Commission, Department of Defense, Department of Energy, Department of Homeland Security, Department of Justice, Department of Transportation (including the Federal Highway Administration), Environmental Protection Agency, Food and Drug Administration, Forest Service, National Aeronautics and Space Administration, National Institute for Occupational Safety and Health, National Institute of Food and Agriculture, National Institute of Standards and Technology, National Institutes of Health, National Science Foundation, Bureau of Industry and Security, Department of Education, Department of Labor (including the Occupational Safety and Health Administration), Department of State, Department of the Treasury, Director of National Intelligence, Nuclear Regulatory Commission, U.S. Geological Survey, U.S. International Trade Commission, and USPTO. Source: The National Science and Technology Council (NSTC), *Supplement to the President's FY 2012 Budget*, 2011.

and responsibilities. The primary goals of this program are to increase the transfer of new technologies from university to industry and facilitate the commercialization of nanotechnology (NNI Strategic Plan, 2011). Federal agencies put coordinated efforts toward identifying specific R&D targets, setting up R&D directions[38] in nanotechnology and expediting commercialization by focusing on applications (NNI Research Direction II, 2004).

Funding is the main mechanism that the NNI uses to achieve its goals by supporting nanotechnology research. The participating federal agencies have pre-allocated R&D budgets for nanotechnology; the publicized NNI budget represents the collective sum of these agency-level budgets. Federal research grants are awarded by individual agencies in accordance with their respective missions. While the NNI utilizes a traditional government funding system, it drives a national strategic plan for nanotechnology with integrated and unified directions across funding agencies. The NNI has been one of the top priorities in the S&T policy agenda that former Presidents have pursued. On January 21, 2000, President Clinton announced the launch of the NNI in a public address at the California Institute of Technology. On December 3, 2003, following up on the Clinton Administration's initiative, President Bush signed into law the "21st Century Nanotechnology Research and Development Act," which guaranteed a multi-year funding into nanotechnology research. To support the interests of these high-profile

[38] An early-stage plan for the NNI had very specific guidelines. For instance, the deliverables in the first five years were to "…develop new standard reference materials for semiconductor, lab-on-a-chip-technologies, nanomagnetics, and calibration and quality assurance analysis for nanosystem first achieved by FY2003… [and to] develop 3-D measurement methods for the analysis for physical and chemical at or near atomic spatial resolution first achieved by FY2004 …" (NNI, *The Initiatives and Implementations Plan*, 2000).

policymakers and respond to the calls by the Act, the NNI needed to make tangible the benefit of increased funding and enforce the requirements of reviews and reporting (Lane and Kalil, 2005). The 2010 budget provides $1.9 billion for the NNI, reflecting a steady growth in the NNI investment (see Figure 1). The cumulative NNI investment by 2011 exceeds $14 billion. This magnitude of budget makes the NNI the biggest U.S. government S&T program since the Apollo Program.

Insert Figure 4.1 about here

The NNI program involves many actors such as universities, government, and industry. From the inception, the NNI has hosted a series of workshops inviting these actors to identify major technological barriers to achieving its goal, which is to promote the economic competitiveness of the U.S.[39] These workshops play a significant role in highlighting the need for targeted funding and in setting up focused research directions by gathering inputs from the scientific community as well as informing strategic plans to it. In particular, these workshops underscore specific research targets and metrics of progress toward those targets and the commercialization efforts for economic growth. For instance, a report from one of these workshop sessions shows strong interests of the participants in licensing, intellectual property (IP) rights, and new business models in nanotechnology (NNI Southern Regional Workshop, 2002). These workshops thus have been an impactful mechanism to propagate the NNI goals within the nanotechnology research community.

[39] Since 2000, the Nanoscale Science, Engineering, and Technology Committee, the subcommittee of the NSTC, has organized over 20 official NNI workshops and, separately, the NNI participating agencies have organized many more workshops that were associated with or supportive of the initiative (NNI, *Strategic Planning Stakeholder Workshop*, 2010).

Workshops typically consist of leading plenary sessions followed by breakout sessions. In plenary sessions, experts in a subject matter share their insights and discussed the current state of specific areas and application domains of nanotechnology research. In breakout sessions, participants brainstorm for each of the NNI goals (e.g., "Foster the transfer of new technologies into products for commercial and public benefit"), discussing, revising and prioritizing pre-defined objectives with a view to achieving these goals.[40] This type of communication should have helped promote ideas that are well aligned with the NNI goals among workshop participants (NSTC, 2010). Our interviews with university nanoscientists who have participated in these workshops confirm that the workshops serve as venues for the participants to obtain information about the most interesting research topics and potential directions for future research. In particular, workshop sessions on specific industry sectors provide hints for university researchers on areas that appear more promising for receiving grants. Our interviewees repeatedly confided that their priority is always on fundable research topics and they often set aside new research ideas that deem less suited for winning grants.

This practical orientation of the NNI is likely to exert disproportionally greater impacts on university research than on the R&D in other institutions because the direction of the NNI-led investments for economic returns presents a starker contrast with the norms of academia such as universalism, disinterestedness and communism (Merton,

[40] Some examples of the brainstorming questions include: "Are there new forms of public-private partnerships that you could recommend to improve commercialization?" "What do you think the NNI should do in regard to improving/fostering technology transfer and commercialization?" "What U.S. Government policies (or lack thereof) are helping or hindering the commercialization of nanotechnology in the United States?" (NSTC, 2010).

1973) that had traditionally discouraged university researchers from engaging in commercialization-oriented activities. Further, and more important for our empirical design, the NNI's initiation on focused research and commercialization appears largely exogenous to the academic community. Though some prominent university scholars provided individual inputs to the NNI's establishment[41], the academic community on the whole seems to have been disinterested in, or unaware of, the specifics of the NNI until its launch. Hence, the NNI can be considered as an exogenous shock to the nanotechnology research community.[42]

The U.S. NNI is probably one of the strongest commercialization-oriented government programs we know of in the early 21st century. Other countries such as Japan, U.K., Germany, and France that are known for their high nanotechnology capabilities did not show a noticeable shift in their nanotechnology policies until 2010, when the U.K. and Germany finally introduced national nanotechnology policies similar

[41] Inputs from these prominent scholars have been general endorsements to nanotechnology as a promising field that deserves aggressive national investments, rather than suggestions of specific research topics to be included in the agenda. For instance, Richard Smalley, a Nobel Laureate in chemistry, concluded in his testimony to the Senate Subcommittee on Science, Technology and Space: "We are about to be able to build things that work on the smallest possible length scales. It is in our Nation's best interest to move boldly into this new field" (NSTC, 1999b).

[42] In fact, the NNI launch seems to have been a "surprise" to most people involved, even to the policy makers. The following quote illustrates this point: " …On behalf of the interagency group, on March 11, 1999, in the historic Indian Hall at the White House's Office of Science and Technology Policy (OSTP), I proposed the NNI with a budget of half billion dollars for fiscal year 2001. I was given 10 minutes to make the case. While two other topics were on the agenda of that meeting, nanotechnology captured the imagination of those present and discussions reverberated for about two hours. It was the first time that a forum at this level with representatives from the major federal R&D departments reached a decision to consider exploration of nanotechnology as a national priority. In parallel, over two dozen of other competing topics were under consideration by OSTP for priority funding in fiscal year 2001. We had the attention of Neal Lane, then the Presidential Science Advisor, and Tom Kalil, then economic assistant to the President. However, few experts gave even a small chance to nanotechnology to become a national priority program. However, after a long series of evaluations, NNI was approved and had a budget of $489 million in FY 2001…" (Roco, 2007, p. 3.11) Our interviews with scientists affirm this point that they were not aware of or interested in the NNI agenda until they were presented with the related funding opportunity announcements, workshops, or news about the NNI.

to the NNI.[43] Japan and France have traditionally focused on industry nanotechnology research and their science policies for nanotechnology remained largely unchanged since late 1980s.[44] We found no evidence of significant shifts in science policy regime for nanotechnology in these advanced countries during the period of our study. Thus, these countries seem to be free of any government initiatives that might have directly affected university nanotechnology research in a similar way that the NNI did to the U.S. universities. Therefore, we consider the NNI as a policy intervention that constitutes a reasonable natural experiment by which we can identify the impact of a government S&T program on university research, relative to the research conducted in other U.S. and non-U.S. institutions.

3 Theory and Hypothesis

3.1 NNI and Knowledge Flows

To the extent that nanotechnology research in university relies on the NNI funding, university researchers are likely to be responsive to the initiative's agenda and, thus, may accordingly align their research with those strategic goals to secure continued funding. For several reasons, we consider this assumption to be reasonable. First, the federal government has been the largest sponsor of university research, providing over

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[43] UK, *Nanotechnology Strategy: Small Technologies, Great Opportunity*, March 2010. http://webarchive.nationalarchives.gov.uk/+/interactive.bis.gov.uk/nano/. Accessed on December 4, 2011. Germany, *Nano Initiative–Action Plan*, 2010. http://www.research-in-germany.de/dachportal/en/v-links-and-downloads-einordnen/downloads/nano/2176/nanobroschuere.pdf. Accessed on December 4, 2011.

[44] For instance, France has developed since 1970 its nanotechnology based on regional industry clusters as a network of micro-nano platforms (MAIT, 2009). The Japanese government has supported the establishment of the nanotechnology industry by building industry consortia such as the Semiconductor Industry Research Institute Japan (*Present Status of Japanese Nanotechnology Efforts*, 1997).

60% of the research budget (Stephan, 2010). Second, funding agencies have influenced the focus of university research by setting up specific goals (Bush, 1945; Nelson, 2004; Mowery, 2009). Third, university nanotechnology researchers compete for NNI-funded grants (Lane and Kalil, 2005). We do not mean that university researchers necessarily change their research direction as radically as from basic research to applied research (Thursby and Thursby, 2003). Rather, we expect that, to qualify for funding, university researchers will pay attention to the NNI agenda in determining their research direction[45] and hence, at the margin, the research outcome will bear out the impact of the program to a measurable extent.

Recall that the NNI focuses on facilitating the application of nanotechnology. One of the NNI's strategic goals is to foster the conversion of new technologies into products for commercial and public benefits (cf. Mowery, 2009). Because solving practical problems often leads to important basic research findings as byproducts, university researchers may be willing to adopt the NNI research agenda that have practical orientations. This motivates the university researchers to pay increased attention to technological developments from the industry (Rosenberg, 1990; Stokes, 1997). That is, when the commercialization-focused program is in place, the university research that inherently seeks no immediate practical application and yet involves greater motives of utility may take the development in the industry as a reference point. This is because the industry is another important institution that possesses knowledge about the current state

[45] For example, when university researchers find a funding program that broadly fits to their research directions, they may adjust the details of their research to meet the specific requirements of that program. Our interviews with nanotechnology scientists in universities confirmed this intuition.

of technology and the opportunities for improvement (Arora and Gambardella, 1994; Etzkowitz and Leydesdorff, 2000). To meet the goal of the funding, university researchers may seek technological inputs from the industry that applies nanotechnology primarily to commercial ends. The industry-generated technology might have information that is fundamentally different from the university-generated technology because downstream technologies tend to be developed in response to market demands (Von Hippel, 1988; Cohen, Nelson and Walsh, 2002). The input from the industry can thus be useful for understanding practical applications of the technology. Therefore, under the NNI, university researchers will have greater motivations to appropriate from technological developments in the industry. The form of this appropriation, however, may not be limited to simply obtaining practical ideas from the industry. University researchers can use any areas of research in which the industry possesses a relatively advanced technology such as methods, tools, and new materials that are essential for solving problems and thereby producing outcomes with implications for practical use.[46] Hence, with the launch of the NNI, university researchers may have looked to the industry technology significantly more than they did before. This has likely resulted in an increase of knowledge flows from the industry to the university. Hence, we hypothesize the following:

[46] For instance, the Atomic Force Microscopy or the Scanning Tunneling Microscopy, which enables researchers to image, measure and manipulate matter at the nanoscale, was first developed by a group of IBM scientists in 1981. Since then, a significant body of university research has relied on this particular technology to develop the next level of technology. The discovery of nanotubes exhibits a similar case. Since the NEC's discovery of multi-walled carbon nanotubes in 1991, nanotubes have become an important topic in university nanotechnology research.

Hypothesis 1: The NNI has likely increased knowledge flows from the industry to the U.S. university in nanotechnology.

3.2 NNI, Research Novelty and Research Scope

The government agenda for facilitating the application and commercialization of technology may have accelerated the privatization of university research outcomes. The privatization of research results is essentially an induced effect by the NNI that emphasizes the connection of its sponsored research to economic activities. For instance, under the NNI, universities are encouraged to file patents on research results or take additional steps toward commercialization such as licensing materials, founding companies, and cooperating with industrial material suppliers or manufacturers.[47] [48] In response to the emphasis on economic values of nanotechnology research, the concern of property rights has likely increased among university researchers who would be otherwise disinterested in pursuing property rights, thereby leading to the increased privatization of their research findings (Demsetz, 1967).

When a certain technology is privatized in early stages of development, the successive generation of diverse and useful derivative ideas may be hindered by the restricted access to prior technology (Dasgupta and David, 1994; Nelson, 2004; Aghion,

[47] Some excerpts from the NNI documents illustrate these points. For example, "…nanotechnology research…, which will drive the creation of new IP and wealth generation through new companies in medical applications…" (Nanotechnology Coordination Office, 2002). According to the 21st Century Nanotechnology R&D Act, the NNI "shall establish metrics for evaluation." Also, prior studies that examined the nanotechnology development used patent data as a direct measure of technological innovation (Roco, 2007, 2011).

[48] The NNI official website advertises their achievements, many of which include the part of "Patent and other steps toward commercialization" (http://www.nano.gov/nanotechnology-initiatives/nano-achievements. Accessed on December 4, 2011). This implies that the NNI considers patenting as an important step toward commercialization.

Dewatripont, and Stein, 2008). As knowledge is accumulated over time, prior knowledge becomes a critical input for new knowledge creation (Fleming, 2001). Imagine the path for technology development as randomly dispersed branching-outs from prior nodes of technology to the next nodes of new technology. These branching-outs to a novel technology occur in a process in which the components of accumulated knowledge are recombined to produce an invention. Thus, accessing prior knowledge is essential for branching out to a new technology. If, for any reason, the access to certain prior technology is restricted, this prior technology cannot be used as an input for future technology developments and, hence, the subsequent branching-out from the technology is discouraged.

We argue that the NNI has reduced the access to prior knowledge generated by university research in nanotechnology and, thus, has decreased the branching-out to a new technology. We suggest two reasons for this expectation: increased secrecy and the incomplete disclosure of research findings. First, with the NNI's commercialization orientation, the privatization of university research may have accompanied by increased secrecy. To maximize the economic value of their research that can be potentially commercialized, university researchers may attempt to protect their findings with secrecy and refrain from making them freely available for future research (Walsh and Hong, 2003; Walsh , Cho and Cohen, 2005; Walsh et al., 2007).[49] University research has been an important open resource for future technology developments. When information sharing of research becomes problematic, the beneficiaries of this open resource face

[49] For instance, university researchers may become less willing to discuss research in progress with those outside their research group (Walsh and Hong, 2003).

restricted accessibility. Patent filings of university research could mitigate the concern for the expropriation risk. However, patenting is generally a step toward commercialization (NNI[50]; Roco, 2011). IP rights such as patents per se do not reduce accessibility of the technology, but commercialization prompted by patenting can do so (Walsh et al., 2005, 2007). When university researchers consider or are involved in commercializing their research, they may increase secrecy to secure at least a part of their research that is critical for commercialization. This is particularly so given that licensed university technologies are typically in an embryonic stage and, hence, their commercialization requires further inputs from university researchers (Jensen and Thursby, 2001). While the increased secrecy reduces the expropriation risk of university research, it hides certain research findings from the map of possible branching-outs to future technology developments.

Second, the commercialization-oriented goals of the NNI may have triggered delays in disclosing, or resulted in partial disclosures of, university research findings. This slows down the accumulation of prior technologies that would otherwise readily become inputs to new recombination. Commercialization activities such as licensing restrict, or at least delay, the disclosure of university research (Thursby and Thursby, 2002, 2003). The NNI as a federal funding mechanism per se does not reduce disclosures because the funding requires the research results to be eventually disclosed as achievements. However, since the NNI emphasizes explicit links to industry and commercialization, university researchers may conceal certain part of information from

[50] http://www.nano.gov/nanotechnology-initiatives/nano-achievements. Accessed on December 4, 2011.

publication, delay disclosures, or deny the request of other researchers to share the research apparatus or intermediate research procedures (Dasgupta and David, 1994; Thursby and Thursby, 2003). The delay or the incomplete disclosure may render it more difficult for some important findings, which could be a stepping stone for new technology developments, to appear on future technology paths. Consequently, the accessibility of prior university-generated knowledge is reduced.[51]

This reduced accessibility will likely lead to fewer branching-outs to new technologies. Such an adverse effect is particularly to be greater for university researchers because open communication has been the norm in academia. It must be disturbing for university researchers that the access to peers' research findings is hindered, or peer researchers delay disclosures. Note that, traditionally, the reward system in academia has depended only on priority (Merton, 1973). There is an inherent tension between full disclosure (to contribute to the accumulation of knowledge) and individual incentives (to win the priority race by reserving some parts of findings for own next research). Nevertheless, university researchers have learned that research is an infinitely repeated game and hence disclosing their findings is a dominant strategy (Dasgupta and David, 1994). By adding a different channel of earning benefits, the encouraged commercialization of university research distorts this reward system and the incentives of university researchers to disclose knowledge. As a result, university researchers will choose to restrict the access by peer researchers if the expected economic

[51] The increased secrecy and incomplete disclosure of research findings may at first appear conflicting with the incentive to publicly disclose the knowledge through patenting and licensing. Note, however, that both are driven by the incentive to appropriate better from those findings, seeking private benefits as against public benefits.

rents from concealment are greater than the expected rents from disclosure. Therefore, while the reduced accessibility of prior technology affects the whole research community that draws on university research as an open source for future developments, it affects university research more significantly than other institutions such as firms, leading to fewer branching-outs to a new technology from university research.

In addition to their impacts on research novelty through reductions in branching-outs to novel technologies, the NNI's commercialization-oriented initiatives may also reduce the scope of university research because these initiatives may induce university researchers to focus more narrowly on commercially viable areas. While branching-out to a novel technology characterizes the propensity to generate new recombination of technological components (Fleming, 2001), research scopes represent the breadth of components that constitute an invention (Lerner, 1994).

Research scopes may well be influenced by government S&T programs that set up the direction of research to align national research efforts to achieve the mission efficiently. For instance, the NNI plans to introduce prototypes, new products, and productive processes according to pre-defined timelines. Through the strategic plan reports, the NNI designates specific agenda for federal agencies and prescribes directions of nanotechnology research based on extensive planning sessions (NNI Research Directions II, 2004; Roco, 2011). Hence, for continued funding, university researchers need to show their "fit" with these directions and generate tangible outcomes in line with the targets. Government research agenda and planning tend to improve overall performance of S&T research (Lane and Kalil, 2005; Roco, 2007; NSTC, 2010). However, these guidelines may drive university researchers to focus on areas in which visible outcomes are anticipated along the pre-defined directions. While the planning and management of technology development might help increase the efficiency of university research in the designated research areas, it may narrow down the scope of research by redirecting research efforts toward specific areas of focus.

From the university researchers' standpoint, narrower research scopes may be preferable because broader scopes increase the complexity in recombining technological components across areas. The complexity tends to amplify the uncertainty in outcomes because the number of unpredictable interactions between components increases (Fleming and Sorenson, 2004). Thus, university researchers may want to avoid uncertainty by reducing the complexity, which will lead to a narrower scope of each project. Further, narrowed research scopes can also decrease branching-outs to a new technology by reducing the inputs for new recombination. The following two hypotheses summarize the discussion thus far:

Hypothesis 2: The NNI has likely decreased the branching-out to a new technology in the U.S. university research in nanotechnology.

Hypothesis 3: The NNI has likely decreased the research scope of the U.S. university research in nanotechnology.

3.3 NNI and Technological Breakthrough Outcomes

A complete prediction for scientific discoveries or technology developments is virtually impossible. Thus, the government-initiated planning and management of research directions is liable to ignore or foreclose opportunities that could lead to technological breakthroughs in university research. Further, due to incomplete information and bounded rationality, even with carefully designed research programs there always remain unconsidered technological paths, some of which would have delivered significant breakthroughs. We define a technological breakthrough as an invention that has significant impacts on subsequent technology developments (Trajtenberg, 1990; Ahuja and Lampart, 2001; Zucker, Darby and Armstrong, 2002; Singh and Fleming, 2010).[52] Achieving technological breakthrough outcomes may also become harder because, under the focused research directions guided by government initiatives such as the NNI, university researchers are likely to reduce exploration. Following the argument in Hypothesis 3, the narrowed research scopes imply that university researchers exploit more the focused areas in which expected results are less uncertain but explore less frequently in areas with greater uncertainty in outcomes. Fewer branching-outs to novel technologies also suggest that university researchers reduce exploration. To branch out to a new technology, university researchers must take the risk of challenging uncertain paths, search across various technological components, and try out untapped recombination of existing technologies. Narrowed research scopes and fewer branching-outs would reflect the reduction in these types of activities. Decreased explorations in university research will lead to smaller variances and, more importantly, fewer outliers in research outcomes (March, 1991). Reductions in both tails in the outcome distribution imply less frequent breakthroughs (March 1991; Singh and Fleming, 2010) as well as fewer failures. Therefore, under the NNI, university researchers are likely to have reduced exploration and thus produced fewer breakthrough outcomes.

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[52] Technological breakthroughs do not necessarily lead to successes in commercialization, though technological breakthroughs are likely to be positively correlated with economic rents (Harhoff, Narin, Scherer and Vopel, 1999). .

We have so far argued that university researchers reduce exploration *outside* the paths designated by commercialization-oriented programs. However, because government programs may encourage university researchers to explore *within* the pre-defined paths, we need to consider if this type of exploration could contribute to technological breakthroughs. Within a pre-defined path, searches and variations may be short-lived because the technological sources that can be combined into a new technology are much more limited than in areas outside the path. The force that drives university nanotechnology research into areas of promising results may improve the efficiency and hence increase the mean value of outcomes or reduce failures, but it is less likely to increase the portion of breakthrough outcomes. Therefore, under the NNI that pursues pre-defined paths for technological development, university researchers are likely to focus their exploration within the paths with less uncertainty, thereby generate fewer breakthrough outcomes. Hence, we hypothesize the following:

Hypothesis 4: The NNI has likely decreased the proportion of technological breakthroughs from the U.S. university research in nanotechnology.

4 Empirical Design

4.1 Overview

To test our hypotheses, it is not enough to simply demonstrate differences in the characteristics of the U.S. university research before and after the launch of the NNI because the differences may be confounded by various factors that could be at play along the lifecycle of nanotechnology. Hence, we care to address an important specification issue, i.e., the counterfactuals. If the NNI changed the nature of university research, the difference between the pre- and post-NNI university research in the U.S. would become clear only when compared with other U.S. and non-U.S. institutions that conducted nanotechnology research but were immune to, or at least less influenced by, the NNI. Thus, we employ a difference-in-differences estimation to isolate the marginal effect of the NNI on the U.S. university research from the influences of generic factors in the development of nanotechnology.

For empirical specifications, we exploit two elements. First, other U.S. and non-U.S. institutions and organizations also conduct nanotechnology research. Thus, we first identify the type (university, industry, and other research institutions) and the nationality (U.S., U.K., Germany, Japan, and France) of nanotechnology research institutions. We chose these four non-U.S. countries because they have the largest numbers of U.S. nanotechnology patents[53] but experienced no significant changes in their science policy for nanotechnology, at least not during the period of our study. As argued earlier, the NNI has likely exerted the greatest impact on university research because it asked university researchers to perform what they have been largely unfamiliar with, i.e., focused research and the commercialization of research outcomes. In contrast, other research institutions, particularly the industry, may have been affected much less by the NNI's emphasis on economic benefits and targeted research because these are essentially what they have been doing routinely. For the analysis, we divide the patents into the "treatment" group (i.e., nanotechnology patents by the U.S. universities) and the "control" group (i.e., nanotechnology patents by all other institutions). To check robustness, we vary control groups by non-U.S. universities or U.S. non-universities. We also experiment with an

[53] Together, they claim over 70% of all U.S. nanotechnology patents filed by non-U.S. organizations during the period of our study.

alternative control group consisting of U.S. university patents in a different technology class.

Second, the NNI began in 2000, which is long after the enactment of the Bayh Dole Act of 1980[54]. Hence, by the time of NNI launch, any impact of this legislation on university research has presumably been stabilized. Thus, we consider the impact of the NNI to be orthogonal to the overall tendency toward commercialization of university research prompted by the Bayh Dole Act. Moreover, while the university research community as a whole seems to have been unaware of the launch or specific goals of the NNI, university researchers learn the direction of the initiative when they find the Funding Opportunities Announcement from the NNI-participating agencies. According to its strategic plan, the NNI seeks to achieve the goals by influencing each member agency's funding opportunities that attract the interest of university researchers. Therefore, the NNI is reasonably exogenous to university research and our difference-in-differences analysis exploits this property.

We construct our dataset using a public trail of nanotechnology research, i.e., nanotechnology patents filed with and granted by the USPTO. At least for three reasons, nanotechnology patent data are suitable for our empirical corroboration. First, patent data provide unique contents such as application dates and technology subclasses. Because each patent lists the application date, which is likely to be close to the time of research, they can provide a basis for systematically measuring the impact of the NNI on research

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[54] The Bayh-Dole Act, enacted on December 12, 1980, enabled small businesses and non-profit organizations including universities to retain the right to inventions made under federally-funded research programs.

characteristics. Moreover, patent data provide the subclass-level technology classification. For instance, the three-digit nanotechnology class 977 covers a collection of 264 distinct subclass references. Subclasses are very useful for capturing technological changes because they provide fine-grained information for technology development (Trajtenberg, Henderson, and Jaffe, 1997; Thompson and Fox-Kean, 2005).

Second, patent citations reflect knowledge flows, though not perfectly (Jaffe, Trajtenberg, Henderson, 1993; Mowery, Oxley, and Silverman, 1996; Gomes-Casseres, Hagedoorn, and Jaffe, 2006). We are aware of the concern that patent citations might be a noisy proxy for knowledge flows due to, for instance, examiner-added citations (Alcacer and Gittelman, 2006). Nevertheless, we draw on a recent study (Jaffe, Trajtenberg, and Fogarty, 2005), which demonstrates that citations and knowledge flows are highly correlated in the aggregate level. Their finding suggests that “aggregate" citations can be used as good proxies for knowledge flows between organizations. Our comparison is conducted at the organization level (i.e., U.S. universities vs. other institutions), which justifies the use of patent citations as a meaningful proxy for interorganizational knowledge flows. Moreover, even if the researcher filing a patent was not aware of the prior art that the examiner searched and added to patent references, these citations nevertheless represent the existence and the ownership of related prior knowledge. Thus, assuming that researchers also search and use the existing knowledge that are contained in sources other than patent documents, we use patent citations as a reasonable proxy for knowledge flows.

Third, there is a well-established tradition in the patent literature of measuring technological breakthroughs by forward citations (e.g., Singh and Fleming, 2010). The intensity of forward citations represents not only a technological significance but also the economic value of a technology such as consumer surplus generated (Trajtenberg, 1990) or the organization's market value (Hall, Jaffe, and Trajtenberg, 2005). This well fits the NNI's goal, which is to improve the economic value of nanotechnology. Hence, we can effectively use forward citations to measure the NNI's impact on the production of technological breakthroughs from university research.

4.2 Data

We identified 5,401 nanotechnology patents filed by the institutions in the U.S., U.K., Japan, Germany, and France from 1970 to 2010, using the USPTO-entitled patents assigned to the Class 977 (Nanotechnology).[55] We downloaded the data from the USPTO website and parsed them, matching patent assignees with organization identifier from Nanobank (Zucker et al., 2007). Since the U.S. patents or pre-grant publications can be classified into 977 only as cross-references or secondary classifications (USPTO, 2005), the Class 977 helps us to identify all patented nanotechnology research across all scientific fields (e.g., physics, chemistry, material science, and biology).

Our data construction also identified: (1) nanotechnology patents that are cited by any of these 5,401 nanotechnology patents (i.e., backward citations); (2) 11,095 subclass pairs under Class 977; and (3) the number of citations made by 2010 to these nanotechnology patents (i.e., forward citations). For the analysis, we used the five-year

[55] In 2005, the USPTO established a new classification reference 977 for nanotechnology and re-classified all relevant patents into this class dating back to 1970. The Class 977 "provides for disclosure related to nanostructure that has at least one physical dimension of approximately 1-100 nanometers; and possesses a special property, provides a special function, or produces a special effect that is uniquely attributable to the structure's nanoscale physical size" (USPTO, 2005). This agrees well with the NNI's definition of nanotechnology (NNI, *The Initiatives and Implementations Plan*, 2000).

window surrounding the year 2001 (i.e., 1997-2001 and 2002-2006) to compare between the pre- and post-NNI.[56]

4.3 Dependent Variables

We utilized four measures of outcomes to test our hypotheses regarding the impact of the NNI on university research.

4.3.1 Knowledge Flows from Industry

We used backward citations to measure knowledge flows (Mowery, Oxley, and Silverman, 1996; Gomes-Casseres, Hagedoorn, and Jaffe, 2006). Specifically, we constructed for each patent a variable that is equal to the number of backward citations made to industry nanotechnology patents divided by the number of backward citations made to all nanotechnology patents. Hence, this measure ranges from zero to one. Notice that the measure is undefined, and hence was treated as missing, for patents that do not cite prior nanotechnology patents. There were 3,091 nanotechnology patents that had at least one backward citation to prior nanotechnology patents.

4.3.2 Branching-Out to a Novel Technology

Because subclasses allow us to examine fine-grained classifications of nanotechnology (Trajtenberg, Henderson, and Jaffe, 1997; Thompson and Fox-Kean, 2005), researchers increasingly focus on the subclass classification of patents to examine technology transfer, technology recombination, and patent scope (Lerner, 1994; Fleming, 2001; Fleming and Sorenson, 2004; Thompson and Fox-Kean, 2005; Fleming, Mingo,

[56] This reduces the number of patents to 3,720 that are actually used for most of the analysis. We also tried four- and six-year windows for robustness checks and obtained very similar results.

and Chen, 2007). A first-ever recombination of two subclasses can be considered as inventing a new aspect of the corresponding technology (Fleming, 2001; Fleming and Sorenson, 2004; Fleming, Mingo, and Chen, 2007). Following this convention, we measured the branching-out to a novel technology by the new recombination of subclasses that a nanotechnology patent established for the first time within the Class 977. For each nanotechnology patent, we then constructed a dummy variable that indicates if the patent incorporates a branching-out.

4.3.3 Research Scope

Subclasses were developed to address the shortcomings associated with defining a technology by a single aspect (USPTO, 2005). Thus, subclass-level classifications convey additional information about the technology within the three-digit class technology. We measured the research scope of nanotechnology by the number of subclasses within the Class 977.[57] Notice that we consider each patent as the unit of research and, hence, treat the patent scope as equivalent to the research scope. If a nanotechnology patent covers a broader scope of research in nanotechnology, it would be classified into more subclasses within the Class 977. Hence, all else equal, a greater number of subclasses imply a broader scope of research underlying the patent.

4.3.4 Technological Breakthroughs

[57] One could alternatively use the number of International Patent Classification (IPC) classes to proxy for patent scope (e.g., Lerner, 1994). However, IPC classes are intended for industry and profession (Lerner, 1994), whereas the U.S. subclass classification scheme is based on the structure and function of technology. Given the interest of our study in the change of technological nature, subclass classifications appear more appropriate.

The patent literature has established forward citations as an indicator of economic, social, and technological success of the patented technology (e.g., Singh and Fleming, 2010). Following this convention, we measured technological breakthroughs using forward citations. Specifically, we first generated the citation distribution of the entire population of U.S. patents (about 3.9 million) granted in 1976-2010. To account for differences in the citation hazard due to timing and technology, we used the residuals recovered from regressing the number of forward citations on primary patent class, application year, and grant year. This adjustment allows us to compare the number of forward citations across patents that were applied for and granted in the same year and in the same technology class. We then computed the z-scores based on these normalized forward citations (*Z_norm*). Finally, we defined a technological breakthrough (*Top5%*) as the patent belonging to the top 5% of the citation distribution (Singh and Fleming, 2010) and assigned '1' to the measure for these patents and '0' for others.

4.4 Independent Variables

The independent variables for the main models are the indicators of the post-NNI period and the U.S. university. The indicator of the post-NNI period, *PostNNI*, signifies whether the patent was filed in or after 2002. We defined *PostNNI* to cover the period from one year after 2001, considering that patents can be applied for only after some research results are achieved. Because the NNI was announced in early 2000 and the actual funding grew significantly in 2001 (see Figure 4.2), it seems reasonable to allow for at least one year of time lag for the NNI to take into measurable effect. The U.S. university indicator, *USuniversity*, represents whether the assignee of the patent is a U.S. university. For the patents that are co-assigned to university and other institutions, we classified them as university patents.[58] We use the interaction term between *PostNNI* and *USuniversity* to identify the hypothesized effects of the NNI on university research.

Insert Figure 4.2 about here

4.5 Control Variables

4.5.1 Non-patent References

The technology associated with each patent has a different degree of basicness or commercialization potential. A more basic or less applied technology may, by nature, be associated with less knowledge flows from the industry and/or receive more citations. Hence, we controlled for this effect by including the number of *non-patent references* in the tests of Hypotheses 1 and 4. We expect that *non-patent references* also capture another effect of academic knowledge on future citations. This proxy for the usage of academic knowledge is highly correlated with citation measures (Ahuja and Katila, 2004; Fleming and Sorenson, 2004). Hence, *non-patent references* control for the effect of academic knowledge on citation measures that we use to examine knowledge flows (Hypothesis 1) and technological breakthroughs (Hypothesis 4).[59]

4.5.2 Claims

We included the number of claims to control for the effect of patent claims on the dependent variables. In particular, we expect that patents with more claims are likely to elicit greater forward citations, more subclass references, and fewer backward citations to

[58] Classifying these patens as non-university patents makes little change to the results.

[59] Because we expect that non-patent references are theoretically orthogonal to the dependent variables that are based on subclasses, the main models testing Hypothesis 2 and 3 do not include this variable as control. Controlling for non-patent references makes little difference to the results.

industry patents. Patent claims reflect the technological originality or the coverage of protection and, hence, may be positively correlated with the novelty, scope, and usefulness of technology. On the other hand, patent claims may be negatively correlated with backward citations to industry patents because the reliance on prior art reduces room for novel claims.

4.5.3 University-Firm Co-patent

We included the dummy for patents that are co-assigned to university and firm to control for the effect of firm-involved university research.

4.5.4 Year-Fixed Effects

We included the application year dummies to capture the temporal effects in the development of nanotechnology.

Table 4.1 provides summary statistics of these variables and the correlations between them. No pair of explanatory variables exhibits a correlation that is high enough to cause a concern of multicollinearity.

Insert Table 4.1 about here

4.6 Estimation Method

For Hypothesis 1, we operationalize the dependent variable as the share of backward citations made to industry patents. Hence, we begin with an OLS specification. As a robustness check, we also estimate the negative binomial model with the number of backward citations as the dependent variable. For Hypotheses 2 and 4, we estimate logit models with the dependent variable indicating whether each patent branched out to novel technologies (H2) or belonged to the top 5% in the citation distribution (H4). For

Hypothesis 4, we alternatively use an OLS estimation that operationalizes the dependent variable as the standard normalized forward citations. For Hypothesis 3, we use a log-log linear model and a negative binomial model. In all models, we report heteroskedasticity-robust standard errors.

Our main empirical model is the following:

$$\text{Dependent Variables} = f\left(\varepsilon_i;\ \alpha_t + \beta_1 PostNNI + \beta_2 US\ university + \beta_3 PostNNI * US\ university\right)$$

where α_t is the year effect, β_j's are the coefficients to be estimated, and ε_i is the error term. Table 4.2 reports the estimation results. For robustness tests, we estimate the following models:

$$\text{Dependent Variable} = f\left(\varepsilon_i;\ \alpha_t + \beta_1 PostNNI + \beta_2 US + \beta_3 PostNNI * US\right)$$

on the university-only sample that consists of U.S. and non-U.S. universities, and,

$$\text{Dependent Variables} = f\left(\varepsilon_i;\ \alpha_t + \beta_1 PostNNI + \beta_2 University + \beta_3 PostNNI * University\right)$$

on the U.S. only sample. We tested on the latter sample to obtain the most conservative estimates. That is because U.S. institutions may be going through the same life-cycle of nanotechnology and, hence, by restricting to this subsample we can address the concern of a confounding effect from differences in the technology life-cycle between countries. Table 4.3 presents the results of these additional estimations.

5 Results

5.1 Previews

We begin by showing some patterns in the raw data without controlling for anything. Figures 3 through 7 illustrate the changes in our measures of the nanotechnology research in U.S. universities as compared to that in all other institutions between the pre-NNI period (1997-2001) and the post-NNI period (2002-2006). For both periods, we computed and compared the unconditional means of the dependent variables for U.S. universities and all other institutions.

Insert Figures 4.3 through 4.7 about here

Figure 3 indicates an overall decreasing trend of knowledge flows from the industry but, if de-trended, U.S. universities may have increased knowledge inflows from the industry after the NNI, more than other institutions did. Figure 4.4 illustrates that the gap between U.S. universities and other institutions in branching out to novel technologies is greater in the pre-NNI period than in the post-NNI period. Similarly, the research scope of U.S. universities declined more rapidly than that of other institutions between the periods (Figure 4.5). Figure 4.6 also suggests a significant reduction in breakthrough outcomes from U.S. universities. Kernel density plots (Figure 4.7) strongly support this interpretation by showing that the U.S. university research in the post-NNI period exhibits a contracted density for the right-tail outcomes. Interestingly, after the NNI, the mean value of the U.S. university research has increased, but apparently at the expense of extreme outcomes in both tails.

5.2 Regression Results

We now turn to the regression results. Models 2-1 (OLS) and 2-2 (negative binomial) in Table 4.2 support Hypothesis 1: the interaction term between *USuniversity* and *PostNNI* indicated a significant increase in knowledge flows from the industry to U.S. universities following the NNI.

Insert Table 4.2 about here

We found support for Hypothesis 2 from Models 2-3 and 2-4. In Model 2-3, the interaction term between *USuniversity* and *PostNNI* suggested a significant reduction of U.S. universities' branching-out to novel technologies after the NNI. We also carefully considered a possibility that, by restricting the access to university research, the NNI may have adversely affected the entire U.S. nanotechnology research community including the industry. Thus, in Model 2-4, we estimated a logit model with the U.S. indicator, *US*, and its interaction with *PostNNI*. This is to see if the U.S. nanotechnology research exhibits a distinct characteristic as compared to that of non-U.S. countries. The coefficient on the interaction term was negative, indicating that, after the NNI, U.S. institutions as a whole generated fewer branching-outs to novel technologies relative to non-U.S. institutions. Models 2-5 (OLS) and 2-6 (negative binomial) in Table 4.2 support Hypothesis 3: the interaction between *USuniversity* and *PostNNI* indicated that, following the NNI launch, the research scope of U.S. universities in nanotechnology has significantly decreased relative to other U.S. and non-U.S. institutions.

Hypothesis 4 was also supported in Models 2-7 (logit) and 2-8 (OLS). In both models, the interaction term between *USuniversity* and *PostNNI* confirmed a significant reduction of breakthrough outcomes after the NNI. The analysis on subsets of the sample, in which the observations were divided into two groups—the above-mean outcome group (*Z_norm* > 0) and the below-mean outcome group (*Z_norm* < 0)—revealed that, in the post-NNI period, "successful" outcomes of the U.S. university research decreased relative to other institutions (Model 2-9), but not their "poor" outcomes (Model 2-10).

To facilitate the interpretation of estimates, we calculated the magnitude of changes in the dependent variables after the NNI launch.[60] In terms of knowledge flows (H1), the industry-to-university knowledge flows for U.S universities increased by 36.1% after the NNI, relative to all other institutions (Model 2-2). Following the NNI, the probability of branching out to a new technology by U.S. universities decreased by 18.5%, relative to all other institutions (Model 2-3). The research scope of U.S. universities was also reduced by 10.2%, compared to other institutions (Model 2-6). The relative decline in technological breakthroughs for U.S. universities (H4) was even more drastic (-44.9%, Model 2-7).

We obtained robust results on subsets of data: the university-only sample and the U.S.-only sample (Table 4.3). Model 3-1 and 3-2 together confirm the post-NNI boost in knowledge flows from the industry to U.S. universities. U.S. universities also reduced the branching-out to novel technologies in the post-NNI period but the reduction was not statistically significant when compared to non-U.S. universities (Model 3-3) or to other U.S. institutions (Model 3-4). These results suggest that, while U.S universities or the U.S. research community as a whole reduced the branching-out in the post-NNI period, U.S. universities and other U.S. institutions are indistinguishable from each other in that effect. Model 3-5 implies that the adverse effects were greater for the U.S. industry's branching-out relative to the industry in other countries. The result of Model 2-5 and 2-6

[60] For logit models (2-3 and 2-7), we first followed Zelner (2009) to calculate the predicted DVs for the pre- and post-NNI, including both the conditional effect of interaction term and the main effect, holding all other variables at their means. We then computed the changes in the relative ratio of the predicted values between the U.S. universities and other institutions. For negative binomial models (2-2 and 2-6), we computed the incidence-rate ratios (IRR) after fitting the corresponding model.

on the research scope was confirmed in the university-only sample (Model 3-6) and the U.S.-only sample (Model 3-7). These models thus support that, after the NNI, the research scope of U.S. universities significantly decreased relative to all other institutions. Finally, results on the U.S.-only sample (Models 3-8 and 3-10) and the university-only sample (Model 3-9) provide confirmatory evidence that the post-NNI period has witnessed significant reductions in technological breakthroughs generated by U.S. universities.

Insert Table 4.3 about here

Our analysis in this section assumes that the timing of the NNI was exogenous. If, however, there existed any pre-NNI trends that were in the same directions as we hypothesized for the post-NNI period, our regressions would be confounded with these pre-trends, resulting in biased estimates. We checked this possibility by running a falsification test with "placebo" treatment effects. Specifically, we first created dummies for each year before and after the treatment year (i.e., 2001), with each dummy taking '1' for U.S. university patents applied for in the corresponding year and '0' for all other patents and years. We then ran the regressions based on Models 2-1, 2-3, 2-5 and 2-7 in Table 4.2.[61] Figures 4.8 through 4.11 plot the coefficients of these year dummies. Though there were some noisy upticks and downticks, none of the graphs seemed to indicate any clear pre-trend and 95 percent confidence intervals in the pre-treatment years always contained zero. Changes in the post-treatment years were also consistent with the

[61] Further controlling for country-fixed effects interacted with time trends made little difference to the patterns observed from models without such controls.

hypothesized directions, though the coefficients appeared somewhat imprecisely estimated.

Insert Figures 4.8 through 4.11 about here

5.3 Robustness Checks

To ensure the robustness of our results, we performed a number of different variations of the analysis.[62] To begin with, we varied time windows for the NNI regime. First, we dropped observations of 2001 because, being a transition period, the year 2001 could represent a turbulent environment characterized by strong initial policy drives and the phenomenal increase in funding (see Figure 4.2). We then re-estimated the entire models with the modified five-year windows (i.e., 1996-2000 and 2002-2006). The results were robust to this variation. Second, we employed four- and six-year windows surrounding 2001 and re-estimated our preferred models for each hypothesis. The results were robust except that the four-year window-based test of Hypothesis 2 lacked significance, though the sign was consistent with the prediction.

In addition, we controlled for country-fixed effects in the estimation and obtained robust results. The only notable changes were that, in Models 2-1 and 2-7, the statistical significance of the coefficient of the interaction term between *USuniversity* and *PostNNI* slightly decreased (to a 5% level).

In testing our prediction on the knowledge flow from the industry (Hypothesis 1), for each patent we excluded from backward citations all patent references that were added by the examiner. With this modified measure of knowledge flow, the interaction

[62] Results of these tests are unreported due to space constraints but are available from the authors.

term between *USuniversity* and *PostNNI* lost significance. However, this alternative specification is problematic because the examiner-added citation data are available only for the patents filed after 2001, rendering the inter-period comparison almost meaningless. Hence, we do not consider this result as convincing evidence for rejecting our hypothesis on knowledge flows.

Finally, we replaced our control group (i.e., nanotechnology patents by U.S. non-university and non-U.S. institutions) with U.S. university patents in the liquid crystal display (LCD) technology. Our choice of this technology field owes to three reasons. First, from the beginning, LCD technology has consistently been commercialization-oriented. Second, to the best of our knowledge, no policy intervention comparable to the NNI has occurred in the U.S. during the course of technology development. Third, the overlap between LCD technology and nanotechnology has been minimal; in particular, none of U.S. LCD patents belonged to nanotechnology. We identified a total of 21,129 patents that were filed with the USPTO from 1971 to 2010.[63] Among them, 201 patents were assigned to at least one of U.S. universities. We first checked if these U.S. university LCD patents exhibited a similar trend during the period of our study. We did not find a similar phenomenon in this technology as we did in nanotechnology. We then compared U.S university nanotechnology patents with U.S university LCD technology patents using a difference-in-differences estimation similar to the one in our main analysis. We used technology-age fixed effects instead of application year-fixed effects to

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[63] We followed Stolpe (2002) and Lee, Kim and Lim (2011) to identify LCD patents using the U.S. patent class 349.

account for the temporal effects due to potentially different technology lifecycles.[64] With this alternative control group, all but H3 of our hypotheses found support (at least at the 10% level). Hence, our original control group appears to perform reasonably well in controlling for the baseline effects.

Our argument for the impact on technological breakthroughs (Hypothesis 4) included that fewer branching-outs and reduced research scopes would lead to reductions in the choice sets available for recombinative efforts of exploration and thereby potentially decrease the likelihood of technological breakthroughs (i.e., mediation effects). Hence, we checked how much of the effect we found on Hypothesis 4 might be attributable to these possible mediation effects of branching out and research scope on the NNI impact on technological breakthroughs. The results showed negative and significant mediation effects. However, the first-order effect of the NNI on technological breakthroughs remained significant and sizeable, validating Hypothesis 4 as an independent mechanism.[65]

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[64] While the LCD technology essentially began in 1968 when RCA discovered a totally new type of electronic display (Kawamoto, 2002 ; Lee et al., 2011), nanotechnology had a breakthrough to start by IBM's invention of the Scanning Tunneling Microscopy in 1981 (http://www.nano.gov/timeline, accessed on November 28, 2012). The gap of start years between two technologies suggests that LCD technology and nanotechnology may be at different stages of technology lifecycle. We computed technology age as 'application year minus 1968' for LCD technology patents and 'application year minus 1981' for nanotechnology patents.

[65] Specifically, we first added to Model 2-7 in Table 2 the variable branching-out to novel technology. The coefficient of this variable was positive and significant ($\beta = 0.387$, $p<0.01$) while that of *PostNNI*USuniversity* remained negative and significant ($\beta = -0.646$, $p<0.05$). We then compared this estimate on *PostNNI*USuniversity* with that in Model 2-7 ($\beta = -0.668$, $p<0.05$) using the two-sample t-test for comparing two means. The test strongly rejected the null hypothesis of coefficient equality ($t = -2.892$, $p<0.01$). We repeated the same procedure for research scope. The coefficient on research scope was also positive and significant ($\beta = 0.105$, $p<0.01$) while that of *PostNNI*USuniversity* remained strongly negative ($\beta = -0.654$, $p<0.05$). The two-sample t-test again rejected the null hypothesis of coefficient equality ($t = -1.824$, $p<0.1$).

6 Discussion and Conclusion

The purpose of this paper is to examine the impact of a specific government program in S&T, namely the NNI, on the knowledge flows and the nature of university research. Our intended contribution is not so much in demonstrating how the program increases research productivity as in understanding how such policy intervention influences the flows and the characteristics of university-generated knowledge. Noting that government S&T programs normally seek to facilitate technology transfer from the university to the industry and promote a strong national innovation system, we examine the U.S. NNI that emphasizes the commercialization of nanotechnology and sets the directions for focused research. Our results suggest that the NNI may have led to unintended consequences in the flow and the landscape of knowledge within the field of nanotechnology. Specifically, we find that, after the NNI, U.S. universities have significantly increased knowledge inflows from the industry, reduced branching-outs to novel technologies, narrowed down the research scope, and become less likely to generate technological breakthrough outcomes in nanotechnology, as compared to other U.S. and non-U.S. research institutions. None of these consequences appear to be consistent with the NNI's objectives.

These findings may remain open to alternative interpretations. First and foremost, the U.S. could be entering the steady state faster, or at least be more advanced, than other countries in nanotechnology, independent of the NNI. Then, what we find might simply be capturing differences in the normal progression of life-cycles which, over time, tend to exhibit diminished room for exploration and curtailed technological outcomes in both tails. However, for at least several reasons, our results are unlikely to be confounded by potential life-cycle effects. At the time of the NNI launch, nanotechnology was considered as being still at an early stage and was not expected to enter a maturity stage until well after 2020 (Roco 2007). A series of documents related to the NNI also describe the NNI as a science project identifying an emerging technology (e.g., NSTC, 1999a; NSF, 2001). In particular, the state of the U.S. in nanoscale science and technology seemed at best on a par with that of other major countries such as the E.U. and Japan (NSTC, 1999a). Our results also survive the additional controls of heterogeneity across countries and technology areas within nanotechnology.[66] Moreover, our results show that, while successful technology outcomes (i.e., breakthroughs) in the U.S. university research significantly decreased, failures (i.e., left-tail outcomes) did not decrease in the post-NNI period. If the technology life-cycle effect purely drove our results, failures too should have been reduced. This asymmetry in the variance reduction in technological outcomes suggests that an exogenous source of variation such as the NNI launch has indeed influenced the U.S. university research. The NNI may have contributed to this asymmetry by selectively funding relatively certain research proposals, thereby leading to more "successful" (but not necessarily breakthrough) outcomes. This, in turn, implies that the (variance-reducing) NNI effect should be greater on the right tail of distribution of

[66] Specifically, we first added dummies for technology categories, country dummies, and the interactions between country dummies and technology category dummies. For technology categories, we used the patent categorization system by Zucker and Darby (2011) that assigns each U.S. patent to one of five broad science areas (i.e., Biology/Chemistry, Semiconductor, Computer Science, Other Science, and Other Engineering), By this, we allow for a different intercept for each country-technology category within nanotechnology. The results remained unchanged. Alternatively, we controlled for country-fixed effects, a time trend and the interactions between country-fixed effects and the time trend. This estimation thus allows the slope to vary across countries, thereby explicitly accounting for potential inter-country differences in technology lifecycle. The results were robust except for the research scope (Hypothesis 3), which was significant only at 10% on a one-tailed test. Results of these tests are unreported due to space constraints but are available from the authors.

technological performance, which is precisely what we find.[67] Our quantile regression confirmed this asymmetry in the shift of outcome distribution: the right-hand side (at 75 percentile) of the citation distribution significantly shrank after the NNI while the left-hand side (at 25 percentile) remained statistically unchanged.

Second, if the relative quality of U.S. industry patents in nanotechnology increased because of the NNI, U.S. universities may start relying more on industry patents not necessarily because of a shift in research direction but because of the higher intrinsic value of these patents as research inputs. It is possible that the NNI may have boosted the quality of nanotechnology patents by U.S. firms, and hence improved the usefulness of these patents as research inputs. However, if U.S. universities “substituted” to industry patents due to the increased usefulness of these patents, it is not entirely clear why other institutions, U.S. firms in particular, did not also switch into these high-quality patents for their research. For the “substitution” to replace the “shift” as an account for our finding in knowledge flow, one has to explain what caused U.S. universities to rely disproportionately more on these “better” patents than all other institutions did. In particular, given that our finding also holds for the U.S.-only sample, it is quite puzzling why U.S. firms did not try to take advantage of these research input as much as U.S. universities did. Hence, the substitution effect is unlikely to have dominated the shift effect in knowledge flows.

Third, the decrease in U.S. universities’ branching-out to novel technology could also result if the U.S. university research has become concentrated over time in specific

[67] Our results are conditional on the research outcome being ultimately granted for a patent and hence the demonstrated reduction in variance following the NNI holds for outcomes that cleared that hurdle.

areas that are commercially more promising, or if the NNI-designated research topics have triggered a “fad” (Abrahamson, 1991) among U.S. university researchers in choosing research projects (i.e., “hot” topics), or both. If these were the case, even if U.S. university researchers did not increase secrecy and hence the access to their prior knowledge was not actually restricted, branching-outs to a new technology in the U.S. university research may still decrease. That is because the increased concentration of research areas or the new fad in topic selection will most likely result in a narrow-down of research scopes while the accessibility of university research may remain unaffected. Though plausible, these alternative mechanisms do not seem compatible with other inter-country differences we observe in the data. For instance, U.S. firm patents exhibited a disproportionally greater reduction in the propensity to cite non-patent references in the post-NNI period, as compared to non-U.S. firm patents. Considering that a majority of non-patent references are the result of university research (i.e., publications in academic journals), this finding implies that the industry’s access to prior knowledge from university research may have become more restrictive in the U.S. than in non-U.S. countries.

Fourth, some of our findings could result if, with the NNI, university researchers have shifted from basic research to more applied work. To the extent that the argument of Arora and Gambardella (1994) holds for a distinction between university research and industry research, university researchers’ shift to applied work following the NNI may produce outputs that are more specific to application-focused problems, more incremental in nature and less widely used by future inventions. These together would then lead to the same phenomena we report in this paper. However, this “domain shift” hypothesis is not inconsistent with our arguments for Hypotheses 2 through 4. In fact, we suspect that the NNI's intention to promote commercialization may have induced a domain shift for at least some of university researchers. We have nuanced this possibility in our discussion of researchers' recognition or concern of economic rents for their research (Section 3.2). Our arguments do not require that university researchers have necessarily shifted research domains with the NNI but are certainly compatible with such shifts.

Fifth, and related to the above discussion, the domain shift hypothesis can be also consistent with our finding of increased university citations to industry patents. That is, changes in citation pattern could result if university research moved closer to industry research in knowledge space.[68] Given our data, we cannot unambiguously determine if such result follows because university researchers increasingly used industry-generated knowledge (while preserving their domains of research) or because they increasingly started working on problem domains that are traditionally of industry researchers. The truth may perhaps lie in between.

From the empirical standpoint, we claim two contributions. First, by identifying the NNI as a natural experiment and exploiting the difference-in-differences design, we improve our confidence in claiming more than just correlations from the findings. This is also our attempted response to the call for a more precise identification based on

[68] Citation rates could also increase if, for instance, the potential pool of patents to be cited grew after the NNI, independent of changes in citation behavior. We tested this possibility by estimating models akin to Models 2-1 and 2-2 except that, instead of the university's citation to industry patents, we used the industry's citation to university patents as the dependent variable. The result showed that, following the NNI, the U.S. industry significantly *decreased* citations to U.S. university patents. These asymmetric changes in citation rates between the university and the industry appears consistent with our interpretation of U.S. universities' increasing, and disproportionate, utilization of industry knowledge, rather than with the overall growth of citation pool.

counterfactuals in measuring the effect of policy interventions in the economics of science (Jaffe, 2006). Second, our econometric approach allows us to measure the changes in the landscape of research such as knowledge flows, branching out to a new technology, research scope, and the generation of breakthrough knowledge within universities as institutions of knowledge production. These changes may not necessarily bring short-term economic consequences but have long-term effects on the economy, which we do not directly examine in this paper. To the proposition that institutional changes imposed on the open science and the political patronage impact the long-term performance of the science and technology community (Dasgupta and David, 1994), we provide robust empirical evidence.

Our study is not without limitations. First, in the analysis of knowledge flows, we used all citations without distinguishing the source of those citations. We believe that this measure reasonably proxies for the actual knowledge flow because, even if the researcher filing a patent was not aware of the prior art that the examiner searched and added later to patent references, these citations still imply the existence and the ownership of related prior knowledge; this piece of knowledge is likely to have been exposed to the researcher perhaps in formats other than patent documents. Nevertheless, we acknowledge that our inability to make the distinction between inventor-added citations and examiner-added citations is clearly a limitation, which we cannot currently address given the lack of data. Second, and more broadly, we treated all universities as if they were identical in patenting strategy. However, considerable heterogeneity exists across universities in the IP policy (such as patenting and licensing), faculty reward system and resource management at technology transfer offices, not to mention of wide variations in faculty/researcher quality (Siegel, Waldman and Link, 2003; O'Shea et al. 2005). Moreover, each university may pursue a different path in the refinement of their IP regime. Our findings are admittedly the aggregate effect across universities, each of which may have been influenced differently by the NNI. Given our empirical design, however, ignoring these differences will be an issue only if all of U.S. universities have simultaneously shifted their IP regimes (and did so specifically for nanotechnology) at the same time as the NNI launch. To the best of our knowledge, there is no evidence of such collective and concurrent shifts. Further, since we do not focus on the quantitative aspect of patenting, our measures of outcomes (except perhaps forward citations) appear less vulnerable to different intensities of patenting across universities. Nevertheless, incorporating these inter-university differences in IP regime might further solidify our results.

Our findings have a significant implication for S&T policies that pursue maximizing national economic benefits. As Figure 4.11 illustrates, commercialization-oriented government programs may exert dual impacts on university research. Under the NNI, the mean value of university research clearly moved upward and poor outcomes decreased, but breakthrough outcomes decreased as well. The government-initiated emphasis on commercialization and focused research directions may improve the average economic payoffs by increasing the outcome efficiency in university research. However, these interventions may undermine open paths toward novel technologies and hinder explorations of unknown fields, thereby reducing the chances of achieving breakthrough outcomes from university research.[69] From the policy standpoint, the NNI has clearly accomplished some of its goals; the inter-agency efforts for nanotechnology development are assessed to have been aligned and structured well to promote commercialization of nanotechnology (NNI Review Committee et al., 2006).[70] However, our study provides evidence that these accomplishments may have been accompanied by potentially unintended changes in the characteristics of university research. Considering that the ultimate goal of the NNI is to achieve the U.S. national leadership of nanotechnology development in industrial competitiveness (21st Century Nanotechnology Research and Development Act), the changing characteristics of university research—particularly the decreases in branching-out to a novel technology and technological breakthroughs compared to other countries—may suggest at least a partial departure from the original intention of the NNI.[71] Hence, these consequences on university nanotechnology research

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[69] An example may help illustrate these potential side-effects. Harvard University, a first-rate nanotechnology research university in the U.S., had nine nanotechnology patents in the post-NNI period. Six of them (67%) heavily cite industry patents (i.e., belong to the top 5% in the number of backward citations to industry patents), have no branching-out to a new technology, and are classified to only one or two subclasses within 977. Moreover, none of these qualify as a technological breakthrough according to our definition. This paints a stark contrast with its pre-NNI performance: Harvard had 18 nanotechnology patents prior to 2002 but none of these patents exhibit the type of the post-NNI pattern. In particular, eight of these pre-NNI patents (44.4%) were technological breakthroughs per our definition. This case, albeit anecdotal, seems to illustrate the kind of effects we demonstrate in this paper.

[70] The report describes that "…NNI-related R&D is world-class and in many instances world-leading, and [that] it is making invaluable contributions to the advancement of knowledge and innovation in the United States"(p.22) and " NNI activities have produced significant advances in these and other application areas and are progressing from fundamental discovery to technological applications and commercialization" (p.36).

[71] An excerpt from the NNI's own assessment alludes to this point in reporting that "as a percentage of nanoscience and nanoengineering published papers, the fraction originating from the United States declined from 40 percent in the early 1990s to less than 30 percent in 2004, whereas U.S.-based entities continued to lead in the number of U.S. patents awarded" (NNI Review Committee et al., 2006, p.5). Given that journal publication has traditionally been a universal, and perhaps preferred, outlet for university research findings, changes in the outlet composition may be at least partly related to the shifts in university research characteristics we advance in this paper.

are not only unexpected in light of the NNI's ultimate goal but may also counter to what university research is generally expected to pursue.

These adverse impacts may well spread to the entire research community, as indicated by the overall reduction in U.S. institutions' branching-out to novel technologies in the post-NNI period. The U.S. research community, the primary beneficiary of knowledge spillovers from U.S. universities, seems to have been affected indirectly by the post-NNI perturbation in the nature of university research. In particular, the reduced accessibility of the U.S. university research in the post-NNI period may have taxed the U.S. industry more heavily than it did the non-U.S. industry by increasing the relative cost of accessing the channels of knowledge acquisition such as publications or formal/informal communications with university researchers (cf. Cohen et al, 2002). The increased secrecy and incomplete disclosure of university research findings raise the effective cost (such as search cost, licensing fees and infringement liabilities) that industry researchers may bear to use these findings. In particular, the program-induced marginal changes in the knowledge flow and the characteristics of university research may significantly reduce knowledge "spillovers" from universities. Considering that the industry R&D has traditionally been the beneficiary of informal knowledge spillovers from university research (Owen-Smith and Powell, 2004), firms may now need to expend unprecedented efforts to recover the benefit from such spillovers. For instance, to access the knowledge that had previously been obtained at little cost, firms may have to engage in more direct and formal collaborations with universities.

Finally, whether or not government S&T programs, in general, attain the social optimum is beyond the scope of our study. After all, the answer depends on the policy decision that sets up objective functions in the domain of science and technology. However, our analysis generally underscores the importance of the immediate disclosure of research results and the autonomy of scientists and engineers in determining the priorities in conducting research in universities (Bush, 1945; Polanyi, 1962; Merton, 1973; Dasgupta and David, 1994; Nelson, 2004).

7 References

Abrahamson, E. 1991. Managerial fads and fashions: The diffusion and rejection of innovations. Academy of Management Review 16(3): 586-612.

Aghion, P., Dewatripont, M., & Stein, J. 2008. Academic freedom, private-sector focus, and the process of innovation. RAND Journal of Economics 39(3): 617-635.

Ahuja, G., & Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal perspective. Strategic Management Journal 22(3): 197-220.

Ahuja, G., & Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22: 521–543.

Alcacer, J., & Gittelman, M. 2004. Patent citations as a measure of knowledge flows: The influence of examiner citations. The Review of Economics and Statistics 88(4): 774–779

Arora, A., Gambardella, A. 1994. The changing technology of technological change - general and abstract knowledge and the division of innovative labour. Research Policy 23: 523-532

Bush, V. 1945. Science the Endless Frontier: A Report to the President on a Program for Postwar Scientific Research. U.S. Government Printing Office, Washington, D.C.

Cohen, W., Nelson, R., & Walsh, J. 2002. Links and impacts: The influence of public research on industrial R&D. Management Science 48(1): 1-23.

Committee to Review the National Nanotechnology Initiative, National Research Council, National Materials Advisory Board, Division on Engineering and Physical Sciences, National Research Council of the National Academies. 2006. A Matter of Size: Triennial Review of the National Nanotechnology Initiative. Washington, D.C. The National Academies Press.

Dasgupta, P. & David, P. 1994. Towards a new economics of science. Research Policy 23: 487–522.

Demsetz, H. 1967. Toward a theory of property rights. American Economic Review 57(2): 347-359

Etzkowitz, H. and Leydesdorff, L. 2000. The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations. Research Policy 29(2): 109-123.

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science 47: 117–132

Fleming, L., Mingo, S., & Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly 52: 443–475.

Fleming L., & Sorenson, O. 2004. Science as a map in technological search. Strategic Management Journal Special Issue 25(8–9): 909–928.

Furman, J., & Stern, S. 2010. Climbing atop the Shoulders of giants: The impact of institutions on cumulative research. American Economic Review forthcoming.

Furman, J., Murray, F., & Stern, S. 2010. Growing stem cells: The impact of U.S. policy on the organization of scientific research. Journal of Policy Analysis and Management 31(3): 661-705.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. 2006. Do alliances promote knowledge flows? Journal of Financial Economics 80(1): 5–33.

Hall, B., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. RAND Journal of Economics 1: 16–38.

Harhoff, D., Narin, F., Scherer, F.M., & Vopel, K. (1999). Citation Frequency and the Value of Patented Inventions. Review of Economics and Statistics 81(3): 511-515.

Jaffe, A., Trajtenberg, M., & Fogarty, M. 2005. The meaning of patent citations: Report on the NBER/Case-Western Reserve survey on patentees. Chapter12. In Jaffe, A., Trajtenberg, M., & Romer, P.(eds.) Patents, Citations, and Innovations: a Window on the Knowledge Economy.

Jaffe, A. 2006. The 'Science of Science Policy': Reflections on the important questions and the challenges they present. Keynote address at the NSF workshop on advancing measures of innovation: Knowledge flows, business metrics, and measurement strategies.

Jaffe, A., Trajtenberg, M., & Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108: 577-598.

Jensen, R., & Thursby, M. 2001. Proofs and prototypes for sale: The licensing of university inventions. American Economic Review 91: 240-259

Kawamoto, H. 2002. The history of liquid-crystal displays. Proceedings of the IEEE 90 (4): 460-500.

Lane, N., & Kalil, T. 2005. The National Nanotechnology Initiative: present at the creation. Issues in Science and Technology 2005 summer.

Lee, J., Kim, B.-C., & Lim, & Y.-M. 2011. Dynamic competition in technological investments: An empirical examination of the LCD panel industry. International Journal of Industrial Organization 29: 718-728.

Lerner, J. 1994. The importance of patent scope: An empirical analysis. RAND Journal of Economics 25 (2): 319–333.

Mansfield, E. 1991. Academic research and industrial innovation. Research Policy 20:1-12

March, J. 1991. Exploration and exploitation in organizational learning. Organization Science 2(1): 71–87.

Martin, B. 2003. The changing social contract for science and the evolution of the university. In: A. Geuna, A. J. Salter and W. E. Steinmueller. (Eds.), Science and innovation. Rethinking the Rationales for Public Funding. Edward Elgar, Cheltenham, UK.

Merton, R. 1973. The sociology of science: Theoretical and empirical investigations. University of Chicago Press, Chicago, IL.

Mowery, D., Oxley, J., & Silverman, B. 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal 17(Winter Special Issue): 77–92.

Mowery, D. 2009. What does economic theory tell us about mission-oriented R&D. Chapter 12. pp. 131-147. In Dominique Foray (ed.) The New Economics of Technology Policy. Edward Elgar, Cheltenham, UK.

Murray, F., Aghion, P., Dewatripont, M., Kolev, J., & Stern, S. 2009. Of mice and academics: The role of openness in science. MIT Sloan Working Paper.

Nanotechnology Coordination Office. 2002. National Nanotechnology Initiatives-Southern Regional Workshop. Nanotechnology: From the Laboratory to New Commercial Frontiers. Rice University. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science Foundation. 2001. Nanotechnology: Opportunities and Challenges, September 10, 2001, University of California at Los Angeles. http://www.nsf.gov/crssprgm/nano/activities/finalreport_ucla.jsp Accessed on December 4, 2012.

National Sicence and Technology Council. 2010. National Nanotechnology Initiative. Research and Development Leading to a Revolution in Technology and Industry. Supplement to the President’s FY 2011 Budget. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Interagency Working on Nanoscience on Nanoscale Science, Engineering, and Technology.1999a. Nanostructure Science and Technology, A Worldwide Study. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Interagency Working on Nanoscience on Nanoscale Science, Engineering, and Technology.1999b. Nanotechnology Research Directions:IWGN Workshop Report, Vision for Nanotechnology R&D in the Next Decade. The White House. Washington. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Subcommittee on Nanoscale Science, Engineering, and Technology. 2004. National Nanotechnology Initiatives-Research Directions II WorkshopNational Academy of Science. Washington, D.C. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Subcommittee on Nanoscale Science, Engineering, and Technology. 2010. Strategic Planning Stakeholder Workshop. Final Report. Arlington, Virginia. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Sicence and Technology Council. 2008. National Nanotechnology Initiative. Research and Development Leading to a Revolution in Technology and Industry. Supplement to the President's FY 2009 Budget. http://www.nano.gov/publications-resources. Accessed on November 4, 2012.

National Sicence and Technology Council. 2010. National Nanotechnology Initiative. Research and Development Leading to a Revolution in Technology and Industry. Supplement to the President's FY 2011 Budget. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Sicence and Technology Council. Committee on technology. Subcommittee on Nanoscale Science, Engineering, and Technology. 2011. National Nanotechnology Initiative. Research and Development Leading to a Revolution in Technology and Industry. Supplement to the President's FY 2012 Budget. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Subcommittee on nanoscale science, engineering, and technology. 2011. National Nanotechnology Initiative Strategic plan. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

National Science and Technology Council. Committee on technology. Subcommittee on nanoscale science, engineering, and technology. 2000. National Nanotechnology

Initiatives-The Initiatives and its Implementations Plan. http://www.nano.gov/publications-resources. Accessed on December 4, 2011.

Nelson, R. 1959. The simple economics of basic scientific research. Journal of Political Economy 67(3): 297-306.

Nelson, R. 2004. The market economy, and the scientific commons. Research Policy 33(3): 455-471.

O'Shea, R.P., Allen, T.J., Chevalier, A., & Roche, F. 2005. Entrepreneurial orientation, technology transfer and spinoff performance of U.S. universities. Research Policy 34(7): 994-1009.

Owen-Smith, J., & Powell, W. 2004. Knowledge networks in the Boston biotechnology community. Organization Science 15 (1):5–21.

Polanyi, M. 1962. The republic of science: Its political and economic theory. Minerva 1 (l): 54-73.

Roco, M. 2007. National Nanotechnology Initiatives-Past, present, and future. In Taylor and Francis(eds.), Handbook on Nanoscience, Engineering, and Technology, 2nd ed., 3:16-26

Roco, M. 2011. The long view of nanotechnology development: the National Nanotechnology Initiative at 10 years. Journal of Nanoparticle Research 13: 427-445

Rosenberg, N. 1974. Science invention, and economic growth. Economic Journal 84(333): 90–108.

Rosenberg, N. 1990. Why do firms do basic research (with their own money)? Research Policy 19(2): 165–174.

Siegel, D.S., Waldman, D., & Link, A. 2003. Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: An exploratory study. Research Policy 32(1): 27-48.

Singh, J., & Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? Management Science 56(1): 41-56.

Stephan, P. 2010. The economics of science: Funding for research, ICER Working paper 12/2010.

Stokes, D. 1997. Pasteur's Quadrant: Basic Science and Technological Innovation. Washington, DC: Brookings Institution Press.

Stolpe, M. 2002. Determinants of knowledge diffusion as evidenced in patent data: The case of liquid crystal display technology. Research Policy 31: 1181-1198.

Thompson, P., & Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: A reassessment. American Economic Review 95(1): 450-460

Thompson, P. 2006. Patent citations and the geography of knowledge spillovers: Evidence from inventor- and examiner-added citations. Review of Economics & Statistics. 88(2):383-388.

Thursby, J., & Thursby, M. 2002. Who is selling the ivory tower? Sources of growth in university licensing. Management Science 48(1): 90-104

Thursby, J., & Thursby, M. 2003. Intellectual property- university licensing and the Bayh-Dole Act. Science 301(5636): 1052-1052

Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovations. RAND Journal of Economics. 21: 172–187.

Trajtenberg, M., Henderson, R., & Jaffe, A. 1997. University versus corporate patents: A window on the Basicness of Invention. Economics of Innovation and New Technology 5: 19-50.

USPTO. 2005. Handbook of Classification.

Von Hippel, E. 1988. The Sources of Innovation. Oxford University Press, New York.

Walsh, J., Cohen, W., & Cho, C. 2007. Where excludability matters: Material versus intellectual property in academic biomedical research. Research Policy 36(8): 1184-1203.

Walsh, J., Cho, C., & Cohen, W. 2005. View from the bench: Patents and material transfer. Science 309(5743): 2002-2003.

Walsh, J., & Hong, W. 2003. Secrecy is increasing in step with competition. Nature 422(24): 801-802

Zelner, B.A. 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. Strategic Management Journal 30(12): 1335–1348

Zucker, L.G. and Darby, M.R. 2011. COMETS Data Description, release 1.0, Los Angeles, CA. UCLA Center for International Science, Technology, and Cultural Policy.

Zucker, L.G., Darby, M.R., & Armstrong, J. 2002. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. Management Science 48(1): 138-153.

Zucker, L., Darby, M., Furner, J., Liu, R., & Ma, H. 2007. Minerva unbound: Knowledge stocks, knowledge flows and new knowledge production. Research Policy 36(6): 850-863.

Table 4.1 Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Knowledge flow from industry (ratio)													
(2) Knowledge flow from industry (count)	0.333												
(3) Branching-out to novel technology	-0.094	-0.051											
(4) (Log)Subclasses (Research scope)	-0.042	-0.016	0.674										
(5) Subclasses (Research scope)	-0.032	-0.009	0.636	0.950									
(6) Top 5% (Breakthrough)[1)]	0.016	0.009	0.074	0.039	0.039								
(7) Z_norm (Breakthrough)	-0.015	0.008	0.075	0.041	0.037	0.720							
(8) PostNNI	0.074	0.093	-0.054	-0.042	-0.044	-0.228	-0.131						
(9) US	-0.072	0.068	0.048	0.025	0.020	0.079	0.113	0.056					
(10) University	-0.083	-0.038	0.043	0.029	0.021	0.040	0.083	0.070	0.256				
(11) US University	-0.083	-0.033	0.046	0.028	0.021	0.050	0.089	0.055	0.303	0.968			
(12) Non-patent references	0.003	0.281	0.001	1.0E-4	-0.001	0.034	0.067	0.094	0.183	0.141	0.150		
(13) Claims	-0.004	0.025	0.010	0.002	0.002	0.103	0.111	-0.033	0.158	0.073	0.081	0.115	
(14) (Log)Claims	0.001	0.025	0.001	-0.010	-0.008	0.095	0.120	-0.028	0.186	0.087	0.096	0.097	0.819
(15) University-firm copatent	0.005	0.026	-0.017	-0.010	-0.002	0.004	0.027	-0.003	0.035	0.219	0.188	0.021	0.034
(16) Total backward citations	0.098	0.491	-0.015	-0.020	-0.022	0.040	0.070	0.063	0.186	-0.039	-0.031	0.619	0.144
N	5401	5401	5401	5401	5401	5401	5401	3720	5401	5401	5401	5401	5401
Mean	0.391	2.331	0.285	0.522	2.054	0.143	0.403	0.502	0.721	0.202	0.192	13.850	20.974
Std. Dev.	0.431	6.426	0.452	0.597	1.483	0.350	1.336	0.500	0.449	0.402	0.394	31.538	17.476
Min.	0	0	0	0	1	0	-1.488	0	0	0	0	0	0
Max.	1	95	1	2.773	16	1	20.647	1	1	1	1	436	296

	(14)	(15)	(16)
(14) (Log)Claims			
(15) University-firm copatent	0.032		
(16) Total backward citations	0.126	0.014	
N	5400	5401	5401
Mean	2.762	0.012	14.403
Std. Dev.	0.795	0.109	28.626
Min.	0	0	0
Max.	5.690	1	406

Notes: 1) Technological breakthroughs are defined as the patents that belong to the top 5% of the forward citation distribution of the entire U.S. patent population (granted in 1976-2010). 2) All correlation coefficients above 0.03 or below -0.03 are significant at 5%.

Table 4.2 Models for the Effect of the NNI on University Research

	(2-1)	(2-2)	(2-3)	(2-4)	(2-5)	(2-6)	(2-7)	(2-8)	(2-9)	(2-10)
D.V.:	Knowledge flow	Knowledge flow	Branching-out	Branching-out	Log (Subclass)	Subclass	Top5%	z_norm	z_norm>0	z_norm<0
Estimation method:	OLS(Ratio)	NB	Logit	Logit	OLS	NB	Logit	OLS	OLS	OLS
USuniversity	-0.273***	-0.331***	0.573***		0.138***	0.137***	0.563***	0.366***	0.504***	0.015
	(0.032)	(0.097)	(0.127)		(0.036)	(0.039)	(0.148)	(0.105)	(0.150)	(0.020)
PostNNI*USuniversity	0.100***	0.309***	-0.354**		-0.113**	-0.108*	-0.668**	-0.374***	-0.571***	0.002
	(0.039)	(0.116)	(0.178)		(0.047)	(0.055)	(0.327)	(0.108)	(0.153)	(0.024)
US				0.411***						
				(0.122)						
PostNNI*US				-0.484***						
				(0.177)						
Non-patent references	-0.001***	-0.003***					0.007***	0.003***	0.004***	1.35E-4
	(1.40E-4)	(0.001)					(0.001)	(0.001)	(0.001)	(1.04E-4)
Claims	-0.001**	-4.87E-4	0.003	0.003		0.001	0.014***	0.006***	0.003**	4.16E-4
	(3.61E-4)	(0.001)	(0.002)	(0.002)		(0.001)	(0.003)	(0.001)	(0.001)	(4.02E-4)
(Log)Claims					0.011					
					(0.012)					
University-firm copatent	0.138**	0.513***	-0.483	-0.247	-0.087	-0.048	-1.061	-0.136	0.003	0.010
	(0.057)	(0.161)	(0.335)	(0.331)	(0.083)	(0.119)	(0.677)	(0.184)	(0.218)	(0.039)
Total backward citations		0.020***								
		(0.001)								
Constant	0.833***	1.088***	-1.232***	-1.430***	0.431***	0.646***	-1.727***	0.324***	1.182***	-0.411***
	(0.026)	(0.096)	(0.138)	(0.162)	(0.048)	(0.042)	(0.150)	(0.086)	(0.132)	(0.024)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.101				0.020			0.054	0.176	0.218
Log-likelihood		-4805.5	-2105.1	-2110.2		-6007.5	-1090.5			
N	2135	2135	3720	3720	3720	3720	3720	3720	2201	1519

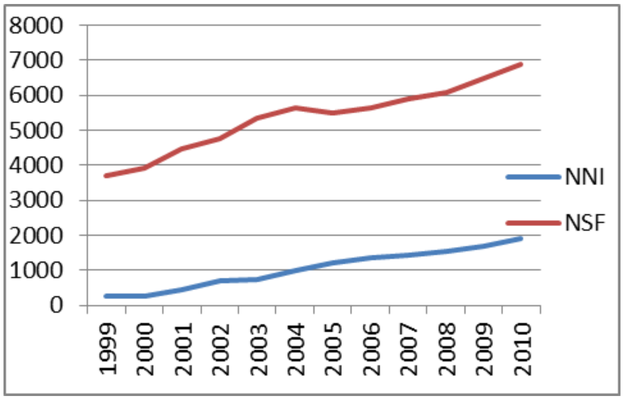
Notes: *PostNNI* is collinear with one of the year-fixed effects and hence is not identified. * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Table 4.3 Models for the Effect of the NNI Estimated on Subsamples (University-only Sample and U.S.-only Sample)

	(3-1)	(3-2)	(3-3)	(3-4)	(3-5)	(3-6)	(3-7)	(3-8)	(3-9)	(3-10)
Sample:	University	US	University	US	Firms	University	US	US	University	US
D.V.:	Knowledge flow	Knowledge flow	Branching-out	Branching-out	Branching-out	Log (Subclass)	Log (Subclass)	Top5%	z_norm	z_norm
Estimation method:	OLS(Ratio)	OLS(Ratio)	Logit	Logit	Logit	OLS	OLS	Logit	OLS	OLS
US	-0.416***		0.554		0.420***	0.287*			0.976***	
	(0.062)		(0.714)		(0.137)	(0.158)			(0.175)	
PostNNI*US	0.335***		-0.349		-0.601***	-0.356*			-0.988***	
	(0.104)		(0.829)		(0.202)	(0.189)			(0.188)	
University		-0.262***		0.477***			0.129***	0.359**		0.241**
		(0.033)		(0.134)			(0.037)	(0.152)		(0.111)
PostNNI*University		0.087**		-0.211			-0.097*	-0.641*		-0.233**
		(0.040)		(0.188)			(0.049)	(0.329)		(0.114)
Non-patent references	-0.001***	-0.001***						0.007***	0.85E-4	0.003***
	(2.92E-4)	(1.40E-4)						(0.001)	(0.001)	(0.001)
Claims	-0.001*	-0.001	0.003	0.003	0.002			0.012***	0.007***	0.005***
	(0.001)	(0.000)	(0.004)	(0.002)	(0.002)			(0.002)	(0.002)	(0.001)
(Log)Claims						0.007	0.020			
						(0.028)	(0.014)			
University-firm copatent	0.151***	0.172***	-0.539	-0.415	-0.151	-0.110	-0.054	-1.000	-0.143	-0.195
	(0.056)	(0.053)	(0.352)	(0.359)	(0.333)	(0.088)	(0.098)	(0.645)	(0.191)	(0.224)
Constant	0.883***	0.818***	-1.118	-1.116***	-1.466***	0.298	0.412***	-1.449***	-0.134	0.475***
	(0.106)	(0.034)	(0.769)	(0.159)	(0.183)	(0.190)	(0.058)	(0.167)	(0.313)	(0.107)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.093	0.101				0.031	0.024		0.077	0.059
Log-likelihood			-498.802	-1585.733	-1457.744			-887.006		
N	524	1619	838	2762	2652	838	2762	2762	838	2762

Notes: *PostNNI* is collinear with one of the year-fixed effects and hence is not identified. We do not conduct the regression of Top5% using the university-only sample because the non-U.S. universities have zero patents with top 5% forward citations. Models 3-1, 3-3, 3-6 and 3-9 use the university nanotechnology patents (both U.S. and non-U.S.); Models 3-2, 3-4, 3-7, 3-8 and 3-10 use the U.S. nanotechnology patents; and Model 3-5 uses the firm nanotechnology patents (both U.S. and non-U.S.). * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

($M)



Source: NSTC, *Supplement to the President's FY2012 Budget*, 2011

Figure 4.1: Trends in the NNI Investment

(%)

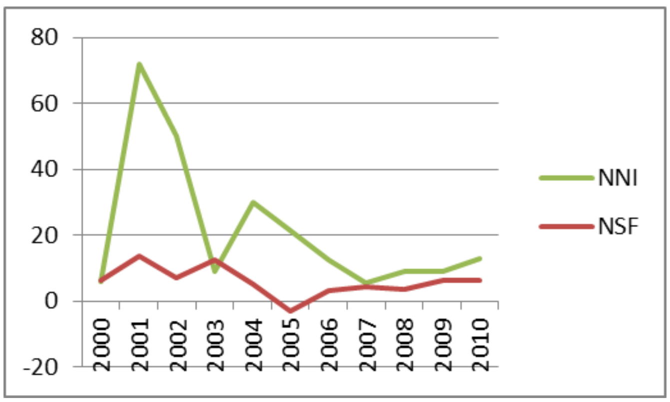
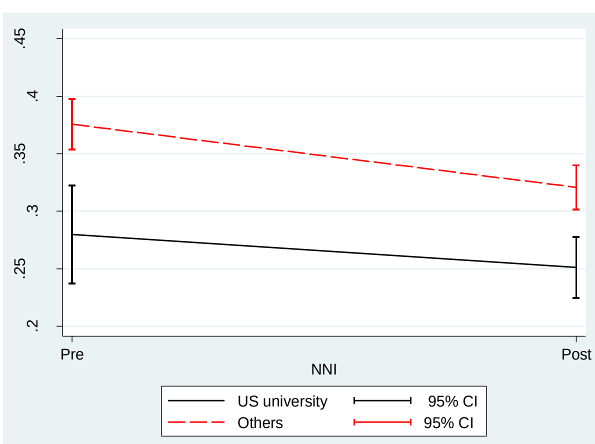


Figure 4.2: Growth Rates of the NNI Funding



Note: '0' indicates the pre-NNI period and '1' the post-NNI period

Figure 4.3: Pre- and Post-NNI Comparison of Knowledge Flows from Industry (Raw Data, Five-Year Window)

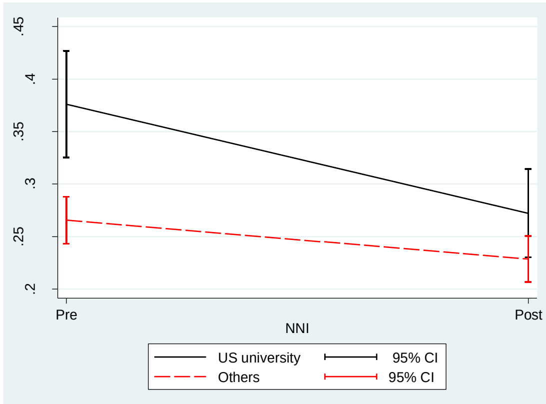


Figure 4.4: Pre- and Post-NNI Comparison of Branching-outs to Novel Technologies (Raw Data, Five-Year Window)

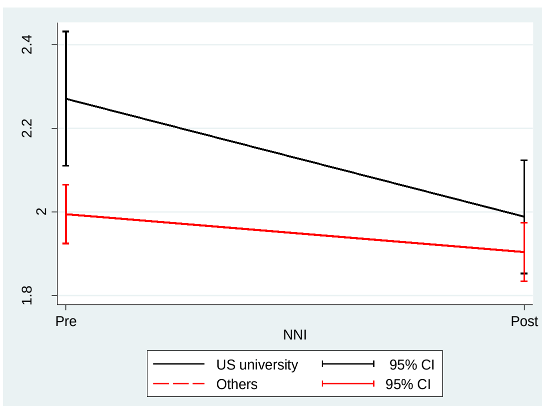


Figure 4.5: Pre- and Post-NNI Comparison of Research Scope (Raw Data, Five-Year Window)

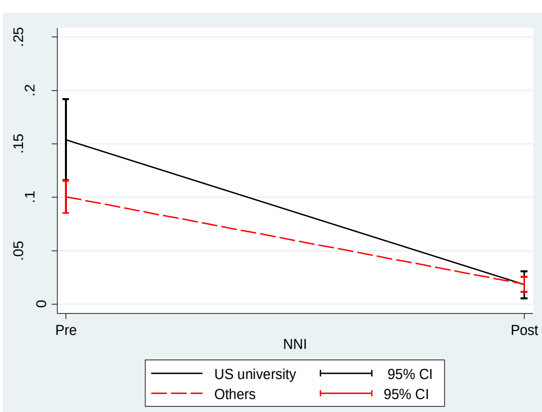
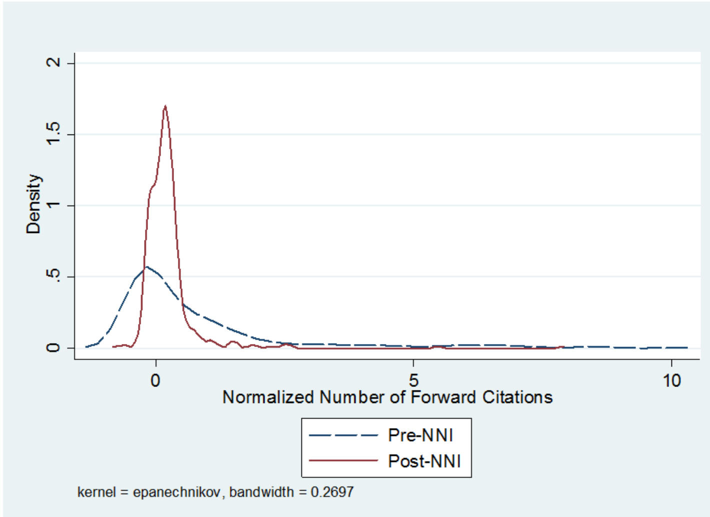


Figure 4.6: Pre- and Post-NNI Comparison of the Proportion of Technological Breakthroughs (Raw Data, Five-Year Window)



Note: *z_normcites* is the standard-normalized number of forward citations made to each nanotechnology patent among all patents applied for and granted in the same year and in the same technology class.

Figure 4.7: Pre- and Post-NNI Comparison of the Distribution of the Number of Forward Citations (Kernel Density)

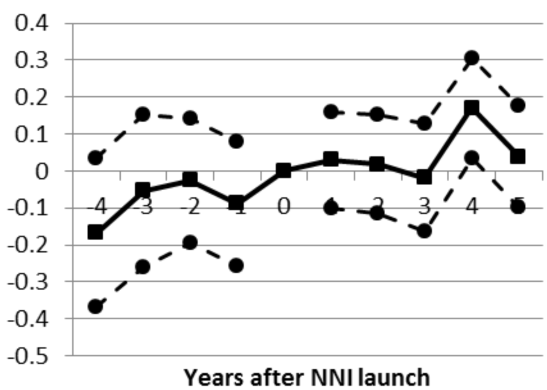


Figure 4.8: Pre- and Post-NNI Effects on Knowledge Flows from Industry

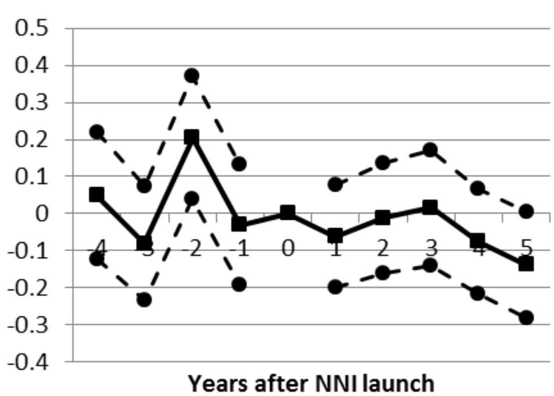


Figure 4.9: Pre- and Post-NNI Effects on Branching-out

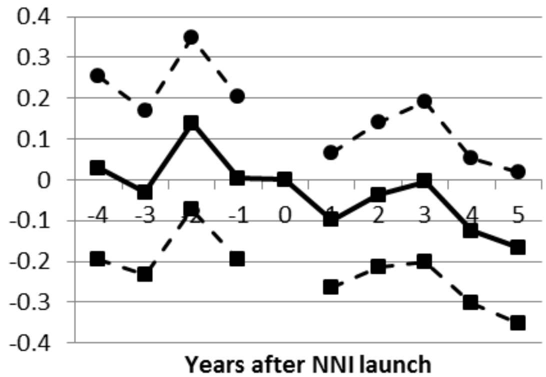


Figure 4.10: Pre- and Post-NNI Effects on Research scope

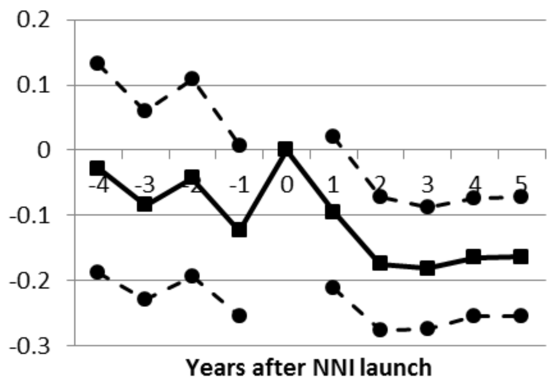


Figure 4.11: Pre- and Post-NNI Effects on Technological Breakthroughs

CHAPTER 4 APPENDIX

Table A4.1: List of Federal Agencies Participating in the NNI

Federal agencies with budgets dedicated to nanotechnology research and development	Agency mission and nanotechnology interest	Budget (FY00-11,$ million)
Consumer Product Safety Commission (CPSC)	Safe use of nanotechnology in consumer products	3
Department of Defense (DOD)	Warfighting capabilities of nation (ex. Novel focal plane arrays and chemical/biological sensors, photocatalytic coatings)	3,586
Department of Energy (DOE)	Solving energy and climate challenges (ex. Energy storage, alternative fuels)	2,700
Department of Homeland Security (DHS)	Enhancement in component technology performance for homeland security application (ex. Materials toolbox, advanced preconcentrators, sensing platform)	45
Department of Justice (DOJ)	Nanotechnology as an integral component of R&D as applicable to criminal justice needs	13
Department of Transportation (DOT, including the Federal Highway Administration, FHWA)	Safety, liable communities, state of good repair, economic competitiveness and environmental sustainability (ex. Innovative materials and coatings with durability)	9
Environmental Protection Agency (EPA)	Protection of human health and the environment by understanding engineered nanomaterials (ex. Environmental sensing, replacing more-toxic substances)	102
Food and Drug Administration (FDA, Department of Health and Human Services)	Protect and promote public health and help ensure the responsible development of nanotechnology	15
Forest Service (FS, Department of Agriculture)	Potential benefit of nanotechnology from the nation's use of renewable resources (ex. Cellulose nanofibers and cellulose nanocrystals)	25
National Aeronautics and Space administration (NASA)	NASA aerospace R&D to reduce vehicle weight, enhance performance and reliability (engineered materials, energy generation and storage, sensors)	348
National Institute for Occupational Safety and Health (NIOSH, Department of Health and Human Services/Centers for Disease Control and Prevention)	Conduct research and provide guidance to protect the health and safety of people exposed to the hazards of an emerging technology (ex. Toxicology studies)	40
National Institute of Food and Agriculture (NIFA, Department of Agriculture)	Lead food and agricultural sciences to help create better future of the nation. Nanotechnology for revolutionary improvement in agriculture and food system	50
National Institute of Standards and Technology (NIST, Department of Commerce)	Develop measurements, standards, and data crucial to a wide range of industries and Federal agencies, (ex. development of new spectroscopic methods to increase in advanced photovoltaics)	923
National Institutes of Health (NIH, Department of Health and Human Services)	Nanotechnology to make valuable contribution to biology and medicine. NIH R&D for nanotherapeutics and diagnostic biomarkers, test, and devices.	2180
National Science Foundation (NSF)	Fundamental nanoscale science and engineering in and across all disciplines. Advance nanotechnology innovations though translational research program by partnering with industry, states, and other agencies.	3,624

Notes: 1) Other participating agencies: Bureau of Industry and Security, Department of Education, Department of Labor (including the Occupational Safety and Health Administration), Department of State, Department of the Treasury, Director of National Intelligence, Nuclear Regulatory Commission, U.S. Geological Survey, U.S. International Trade Commission, and USPTO; 2) Budget data include estimation or projected budgets for some period and do not include Congress direct budge ($548M by DOD and $10M by NASA).
Source: The National Science and Technology Council (NSTC), Supplement to the President's FY 2012 Budget; 2011; The National Science and Technology Council (NSTC), Supplement to the President's FY 2009 Budget; 2008; The National Science and Technology Council (NSTC), National Nanotechnology Initiative. Strategic Plan, 2011; Roco, 2007