12-19-2009

Uses and Nonuses of Patented Inventions

Taehyun Jung
Georgia State University

USES AND NONUSES OF PATENTED INVENTIONS

A Dissertation
Presented to
The Academic Faculty

By

Taehyun Jung

In Partial Fulfillment
Of the Requirements for the Degree
Doctor of Philosophy in the
School of Public Policy

Georgia Institute of Technology and Georgia State University

August 2009

USES AND NONUSES OF PATENTED INVENTIONS

Approved by:

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

Dr. Diana M. Hicks
School of Public Policy
Georgia Institute of Technology

Dr. Philip Shapira
School of Public Policy
Georgia Institute of Technology

Dr. Gregory Lewis
Andrew Young School of Policy Studies
Georgia State University

Dr. Marco Ceccagnoli
College of Management
Georgia Institute of Technology

Date Approved:
April 24, 2009

To my beloved parents

ACKNOWLEDGEMENTS

This dissertation was written in three cities in three different countries: conceived in Atlanta; shaped in Brighton, U.K.; and finalized in Karlsruhe, Germany. Along the long journey (both literally and figuratively) of writing a dissertation, Professor John Walsh, my advisor, was always with me, showing me the way when I was lost and cheering me up so I could overcome the ordeals that I faced. I am deeply thankful to him for his guidance and support. I also thank my committee members (Dr. Diana Hicks, Dr. Marco Ceccagnoli, Dr. Philip Shapira, and Dr. Gregory Lewis) and Dr. Aldo Geuna (University of Sussex) for their valuable comments and insights. Rainer Frietsch at Fraunhofer Institute of Systems and Innovation Research generously provided resources and support for me to finish up the final round of data gathering and analyses. Colleagues and friends of "Walshlab" provided me valuable comments at several milestones during the process of dissertation writing. Certainly, this journey would have been much lonelier and less pleasurable had it not been for the refreshing conversations and joyful moments with my dear friends at Georgia Tech, Georgia State University, the University of Sussex, and the Fraunhofer ISI. I wish to thank all of them.

Finally, my greatest thanks go to my parents, who love and trust me always. I thank them for being my mom and dad. I also thank my sister, Kyung Ah, for her love and prayers, and my niece, Celine, for all the laughs she gave me.

This dissertation was partially supported by the Dissertation Improvement Grant of the National Science Foundation under Grant No. 0823372.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CIS	Community Innovation Survey
CMS	The 1994 Carnegie Mellon Survey of Research & Development
EPO	European Patent Office
GMM	General Method of Moments
GT/RIETI	Georgia Tech/ Research Institute of Economy, Trade and Industry of Japan
IIA	Independence of Irrelevant Alternatives
IPC	International Patent Classification
JPO	Japanese Patent Office
KBV	Knowledge-Based View of a firm
LCD	Liquid Crystal Display
Mkt4T	Markets for Technology
NAICS	North American Industry Classification System
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
OST/INPI/ISI	The Obsevatoire Science et Technology/ Institute Nationale Propriete Industrielle / Fraunhofer Institute of Systems and Innovation Research
PATSTAT	EPO Worldwide Patent Statistical Database
PatVal-EU	European Inventors' Survey

PRO	Public Research Organization
PRT	Property Rights Theory
R&D	Research & Development
SIC	Standard Industry Classification
TCE	Transaction Cost Economics
TPF	Triadic Patent Families
USPC	United States Patent Classification
USPTO	United States Patent and Trademark Office
VIF	Variance Inflation Factor

SUMMARY

Innovation comprises the processes of invention and commercialization. While the importance of innovation, especially commercialization, has been widely recognized, existing studies have largely overlooked the commercialization process. By examining the determinants of uses and nonuses of patented inventions from firms at the levels of technology, organization, and project/invention, this study attempts to help fill a critical gap in the literature. In doing so, it enriches theoretical understandings of innovation and, in particular, builds on the evolutionary explanation of technology development, the Teecian framework on profiting from innovation, Transaction Cost Economics (TCE), the Knowledge-Based View (KBV), and open innovation and innovation network perspectives. It also reveals an empirical reality of commercial use and strategic nonuse of patents. The study is based on a novel dataset constructed from multiple sources: inventor surveys, the United States Patent and Trademark Office online database, and COMPUSTAT, among others.

After examining the factors affecting overall propensity to commercialize patented inventions, this study explores the factors that affect the organizational paths of commercialization. The empirical estimation indicates that technological uncertainty and a strong internal position of complementary assets raise the propensity for internal commercialization. The study argues that openness of innovation processes and network relationships should affect the choice of commercialization paths. Consistent with the

hypotheses, empirical estimations show that external industrial knowledge increases the propensity of internal commercialization. The study also indicates that collaboration has diverging effects on the choice of commercialization paths. While collaboration with firms in vertical relationships tends to favor internal commercialization, collaboration with firms in horizontal relationships tends to favor external commercialization (licensing, start-up).

Finally, the study reports findings on the strategic use of patents and then tests hypotheses about the factors driving strategic nonuse. It concludes that a significant portion of U.S. patents are indeed filed for strategic reasons. It also finds that characteristics of technology and firms are significantly associated with different strategies. In particular, firms are more likely to use a patent for strategic defensive purposes when they have larger amounts of assets. The study concludes with discussing managerial and policy implications.

CHAPTER 1. Introduction

Innovation has played increasingly important roles in both national and industrial competitiveness (Cantwell, 2005). Along with the global trend toward the knowledge-based economy and globalized competition, building up innovation capabilities is taking the central place in the agendas of policy makers as well as firms. Technological innovation is, by definition, a new technology (or a new combination of existing technologies) *put into (commercial) use* (Afuah, 2003; Roberts, 1988; Schumpeter, 1942). Thus, innovation processes complete only when new ideas or a new combination of existing technologies ("invention process") are transformed into commercial applications ("commercialization process"). In practice, two processes are often carried out in an intermingled and iterative way. Nevertheless, they require distinctive focus, skills, resources, and other capabilities to be successfully carried out (Roberts, 1988; Teece, 1986). Schumpeter (1942) clearly pointed out the distinctiveness between them by stating that invention "does not necessarily induce innovation, but produces of itself … no economically relevant effect at all." Commercializing inventions is an important issue both in practice and in theory. Economic and social impacts of innovation can be identified only if the whole innovation processes are taken into consideration. Certainly, inventions of no or little commercial use may generate value to the society by contributing to the progress of science and technology. However, ultimate economic and social benefits will be realized when they are linked to some real-world applications. For

example, competitiveness crisis of the United States in the 70s and 80s was driven not by the lack of generating new scientific and technological ideas but by ignoring commercialization processes of them.

In studying innovation, patents are one of the most important sources for numerous reasons. First, patentability requires novelty, non-obviousness, and, commercial applicability which conforms to the meaning of innovation, especially the inventive part of innovation. Second, by law in most countries, patentability is rigorously scrutinized by professional examiners and the results are published for public access. This enhances reliability of the data. Third, patent publications are well maintained and easily accessible. In many countries, patent data are available as a form of online databases and regularly updated and corrected by the patent authorities. Most of all, rapid increase of patenting and patent propensity (or propensity for an invention to be filed for patents) (Kortum and Lerner, 1999; van Zeebroeck et al., 2008) has enhanced the coverage and comprehensiveness of patents data. While an invention being patented indicates that the invention has a certain level of technological quality and commercial potential it does not, however, indicate whether and how the invention is commercially exploited nor how much commercial value it has, which is an essential information required to evaluate the whole innovation processes.

Intellectual property policy, especially patent policy, is an important policy instrument affecting innovation. Patent systems were designed to promote the progress of scientific and technological knowledge. A core mechanism is to promote investment in new

technology and its commercialization by allowing temporary monopoly over the technology developed as such. However, patents in the contemporary world play much diverse roles, some of which may not necessarily serve to the design goal of the patent systems. For example, patents are used as a tool for hindering competitors' technological advancement as well as securing exclusive rights on own uses. Hence, the growth and extended usage of patents have brought up new possibilities and threats to the systems of innovation. While diversified ways of profiting from patents may promote investment in research and development and division of innovative labors, increase of non-practiced patents may work as an thicket or fence to ultimately retard innovation (Heller and Eisenberg, 1998; Shapiro, 2000). Some would benefit from enlarged opportunities but some others would suffer from additional investment required for developing alternative technologies or from additional payment for licensing or infringing others' patents. This complex and diversified development of patent uses casts a fundamental question on the effectiveness of the current patent systems and has ignited the debates about the patent systems reform. In sum, studying uses and nonuses of patents is of crucial importance for innovation policy.

While the importance of commercializing inventions (and especially commercial and strategic uses of patented inventions) has been recognized for a long time, it has not been reflected in empirical studies of the innovation literature. Most empirical literature has focused on the invention process of innovation and, thus, overlooked the commercialization process. More severely, many studies regard invention and innovation as equivalent concept. Certainly, invention process must play a significant role in

innovation but, as we argued above, it can provide only a partial picture. In inventions being transformed into commercial application, technological superiority is neither a necessary nor a sufficient condition. By examining commercialization process, this dissertation attempts to fill this gap in the literature and provide empirical evidence to the current discussion on innovation and patent policy.

This study examines the determinants of uses and nonuses of patented inventions from firms. We focus on firms because firms account for the largest share of patented inventions and play the protagonist's role in the scene of commercialization. Patented inventions are appropriated in various ways. First, they can be integrated in commercial products. Enhanced or novel product functionality, more efficient manufacturing processes, or enhanced product development processes driven by a new technology rewards the integrator with enhanced product competitiveness and profitability. This is a traditional use of appropriating patented inventions. We call this mode of uses as "internal commercialization". Second, patented inventions can generate direct revenue to the inventor in the form of licensing royalties when they are traded in the market for technology. In other cases like cross-licensing the rents are represented as an access to the technology owned by others. This mode becomes more and more important because all the technology components required for making a product tend to be hardly kept within a single organization as product technology becomes more complex and patenting becomes more pervasive. Because the first-hand benefits from the invention are generated by external parties and then a part of them transferred to the inventor organization, we call this mode as "external commercialization". In some rare cases,

patented inventions become an important instrument to start a joint venture or a new company. This form of appropriation is also categorized as external commercialization.

Patent nonuse can be broken down into two classes: strategic nonuse and other nonuse. Some patented inventions that are not integrated into products or sold in the market for technology may generate strategic rents. In the discrete industry where products are built on relatively small number of technologies, development of substitutable technology by competitors will be a big threat to the owner of original technology. For example, in pharmaceutical or polymer industries, profits from a particular chemical material of a certain effect will not accrue to the original inventor if he fails to prevent alternative methods of synthesis to lead to a material of the same effect. In this industry, the original inventor often files for "fence" patents to prevent competitors from inventing-around the own technologies (Cohen, Nelson, and Walsh, 2000). In the complex industries where large number of technologies is integrated into a final product, such as electronics or semiconductors, patents are often filed to block competitors from further developing the downstream complementary technologies (Cohen, Nelson, and Walsh, 2000). Either case benefits the filer of fence or blocking patents with strategic rents as represented by hindering entry to a certain product market or blocking or slowing down competitors' innovation processes. Some blocking patents are used strategically for the advantageous position in negotiation of future cross-licensing deals (called "bargaining chips" or "player strategy"). The rest of nonuse patents are classified as "other nonuse", albeit its diversity. The classification of uses and nonuses of patented inventions are summarized in Table 1.1.

Table 1.1 Uses of patented inventions

First-hand benefits generated by	Types of benefits		
	Commercialization	Strategic rents	Others/none
Inventor's own organization	Product/Process Research tool	Preventing inventing around (fencing) Blocking	Signaling to investors Reduce potential litigation risk
External/ new organization	Licensing and cross-licensing New company	"bargaining chips" or "player strategy"	Spillovers/leakage
None	NA	NA	Sleeping patents

The first part of this study examines the propensity of commercialization. According to the classification shown in the above table, we examine the factors affecting the patents between the first column (i.e. internal and external commercialization) and the right two columns (i.e. all types of nonuses). In particular we submit novel arguments that the evolutionary stages of technology development and the strength of alternative appropriability would affect the commercializing patented inventions. We argue that the patented inventions in mature technology are easier to find a path to commercial applications because of incremental nature of innovation and lower uncertainty. Also, we argue that the patented inventions from capital intensive firms are less likely to commercialize because of the presence of alternative competitive advantage, progressively increasing organizational rigidity with size, and larger protective value than commercialization value of patents. We also argue and test how a characteristic of product technology influences on this relationship. Our empirical results drawn from a U.S. inventor survey support both hypotheses.

The second part addresses the factors affecting internal and external commercialization paths (the first and the second row of the first column of Table 1.1). Departing from Teecian framework on the profitability of innovation (1986, 2006), we submit enriched arguments incorporating Transaction Cost Economics, KBV, open innovation and innovation network theories. This part pictures an empirical reality of the market for technology and contributes to theoretical and empirical aspects of theories relevant to the market for technology and organizational trajectories of innovation.

The last part takes a detail look on the nonuse patents. In particular, we focus on the strategic nonuse patents (middle column of Table 1.1). Strategic nonuse patents had attracted attention from both policy makers and academic researchers because of their negative potential to innovation. We first show how the strategic nonuse patents are associated with various firm- and industry-level characteristics in our sample. Then, we submit and test the hypotheses about how financial and technological assets of a firm affect the propensity of strategic nonuse. We also submit and test a hypothesis about the impacts of bargaining failure and technological uncertainty on strategic nonuse.

This study takes advantage of both direct and indirect measures of innovative activities using a data set constructed from multiple information sources including patents, a large-scale inventor survey and financial information of firms. Our sample covers patenting firms across multiple industries in the United States.

Previous innovation surveys such as the Yale survey of 1983 (Levin, 1988; Levin, Cohen, and Mowery, 1985; Levin et al., 1987), the Carnegie Mellon Survey of 1994 (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000, 2002), the recent PATVAL survey in Europe (Gambardella, Giuri, and Luzzi, 2007; Giuri et al., 2007), and the Community Innovation Surveys in Europe have provided many valuable insights on innovation. We use our inventor survey to expand our understanding innovation on this tradition. This study will also have the broader impact of contributing to current policy debates on patent reform, which currently suffer from a lack of systematic data on the uses of patents.

Next chapter reviews the relevant previous works. Then, subsequent Parts follow. The final chapter summarizes the findings from all Parts, draws overall policy and managerial implications and then discusses some limitations and avenues for future research.

CHAPTER 2. Literature Review

2.1. Invention, Patents, and Innovation

Innovation has played increasingly important roles in both national and industrial competitiveness (Cantwell, 2005). Along with the global trend toward the knowledge-based economy and globalized competition, building up innovation capabilities is taking the central place in the agendas of policy makers as well as firms. In order to understand innovation, scholars widely depend on patent information—probably because of an increasing number of patent filings, legal linkage of patentability to commercial applicability, quality screening attributed to the well-established patent examination procedures, and publicly accessible databases. Due to well-maintained and readily accessible patent databases, various aspects of innovative activities are captured through patent indicators, which are constructed from published patent documents. Ever since Schmookler (1954) examined American inventive activity using patents, patent indicators have contributed to our better understanding innovation.

Intellectual property policy, especially patent policy, is one of the most important policy instruments affecting innovation. Patent laws in the United States were introduced more than 200 years ago to promote the progress of scientific and technological knowledge.

The U.S. Constitution explicitly gives Congress the power "to promote the progress of science and useful arts, by securing for limited times to authors and inventors the exclusive right to their respective writings and discoveries" (U.S. Constitution, Article I Section 8). However, the patent system in the contemporary economy does not stay within this traditional role but expands its influence on innovation in various ways. As patents move toward a more central position in innovation strategy, more versatile uses of patents are discovered. Now, a patent is not only a tool for securing exclusive rights to commercialize the invention covered by the patent, but also a tool for selling the technology, inducing investment, and hindering competitors' technological advancement.

The growth and extended usage of patents, thus, bring up both a new possibility and a threat to innovation. Increasing investment in new technology and rapid growth of the market for technology may promote innovation. However, an increase in the number of patents, especially non-practiced patents, may retard innovation by fundamentally preventing a new firm from participating in some product markets because they are protected by a thicket of patents or because potential new competitors would incur additional development costs . The role of patents in promoting innovation is indeed a significant policy and legal issue. In *eBay Inc. et al. v. MercExchange* (2006), the Supreme Court denied the categorical application of an injunction, admitting that some patents are intended to be licensed or to be used for blocking competitors. In *KSR International v. Teleflex* (2007), the Supreme Court emphasized a broader interpretation of obviousness (as a way of invalidating a patent). These two legal cases implicitly admit the potential negative impact of strong patent on competition and innovation, and the

decisions can be seen as weakening the strength of patents. Similarly, Congress is currently debating patent reform, including how to improve the patent system to promote innovation rather than retard it. In sum, the study of patents in the context of their commercial usage is a critical issue for contemporary science and technology policy.

Despite all the virtues of patent indicators, they are far from perfect in capturing innovative activities. Two major weaknesses are especially prominent. First, only a portion of all inventions that may contribute to economic and commercial application and scientific and technological advancement is patented. The recent explosion of the number of patents is not necessarily linked to an increased propensity for patenting. The existing studies do not reach a unified explanation behind this phenomenon (Hall, 2004; Hall and Ziedonis, 2001; Kortum and Lerner, 1999; van Zeebroeck et al., 2008; van Zeebroeck, van Pottelsberghe de la Potterie, and Guellec, 2006). According to survey-based research, many innovative companies adopt non-patent appropriability schemes, such as secrecy or complementary capabilities (Cohen, Nelson, and Walsh, 2000; Levin et al., 1987). The Carnegie Mellon survey in 1994 reported that only 20 to 30% of innovations are protected by patents (Cohen, Nelson, and Walsh, 2000). So, do all these stories tell us that patents are not appropriate in studying innovation? Our answer is that patents are still a useful and powerful vehicle to lead us to understanding innovation. While there is no confirmatory evidence that patent propensity has decreased over time, there is plenty of evidence that firms utilize patent systems more heavily and more diversely. In this sense, even without understanding entire invention activities, which look almost impossible to capture, patents should explain an important subset of inventive activities. Thus, we

conclude that the first point raised as a weakness of patents in understanding innovation does not degrade the importance of patents in innovation studies.

Innovation is generally recognized as a coupling of invention with commercialization (Afuah, 2003; Roberts, 1988). Schumpeter emphasizes this point by asserting that invention "does not necessarily induce innovation, but produces of itself … no economically relevant effect at all" (Schumpeter, 1942, p. 84). The fact that an invention is patented indicates that the invention is successful and *commercializable* because it must have passed patentability tests (which include quality, novelty, non-obviousness, and the potential for commercial application). However, patents per se do not tell anything about how the patented invention is or will be commercially exploited. In order for an inventor to commercialize his inventions, he needs to put an enormous amount of effort, often composed of skill sets different from those required for invention, into additional research to transfer the inventions into manufacturing (Roberts, 1988). Therefore, patent indicators may be not only a bad proxy for innovation (Harhoff et al., 1999; He and Deng, 2007; Jaffe, Trajtenberg, and Fogarty, 2000; Lanjouw, Pakes, and Putnam, 1998) but also an indicator of something innovative that is not an innovation. Most innovation research based on patent information has overlooked this critical last step of innovation.

Survey methods overcome some of the weaknesses of patent indicators. By asking directly to inventors or other persons knowledgeable in the innovation process, surveys

can reveal detail information about motives, background, processes, outcomes, or contexts of a particular invention or innovation.

However, patents are neither a perfect measure of innovation nor a technological change. First they are only a subset of invention. And a patented invention is not necessarily innovation in the sense that it is not commercialized. Although the patent propensity is reportedly increasing recently in the U.S. and other countries, secrecy still is regarded as an important means of appropriation. Moreover the usages of patents to contemporary firms are much more diversified now than in the past. More seriously, patents of today are utilized for a variety of purposes beyond their original role—a protective role for commercialization. These include licensing, enhancing the position of negotiation, blocking competitors' technological advance, signaling technological competence to employer or investors, or misleading competitors (Langinier, 2005).

2.2. Commercialization of Patented Inventions

Firms invest their valuable resources into inventive activities because they expect to benefit from the results or process of invention. The benefits from innovation, however, do not accrue automatically to the innovator. Intellectual property rights, especially patents, traditionally have been recognized as the most important legal instrument to enhance the appropriability of innovation. By excluding the rights of use of an invention, patents enable an inventor to secure temporary monopoly status over the invented

technology. Other than patent, an inventor can use numerous mechanisms to appropriate the profit from the invention.

2.2.1. Appropriability Mechanisms from Iinnovation

Schumpeter (1942) pointed out two such mechanisms that critically affect the appropriability of innovation: scale economy of production and market power.[1] When the volume of a product is large, the unit cost for innovation invested for product development spreads more thinly over products and, thus, the amount of profit for a given investment will be large (Cohen and Klepper, 1996b). Appropriability will also enhance if the product market is protected by an entry barrier or market power. Schumpeterian arguments of appropriability have been massively tested, though indirectly, by studying the relationship of the rate of innovation to the firm size or market structure. The empirical results are largely inconclusive; These will be reviewed later in another section. Although briefly referred to here, Schumpeterian appropriability focuses on the product's market conditions and competitive environment. And by focusing on them, Schumpeter relatively ignores the firm-level mechanisms (such as lead time or secrecy) that can enhance product market position or reduce the possibility of imitation by competitors (Winter, 2006). However, several recent surveys consistently found that firm-level mechanisms are indeed important appropriability mechanisms.

[1] Schumpeter meant these two separate elements when referring to "large monopolistic firm."

Both the Yale survey (Levin et al., 1987) in 1983 and the Carnegie Mellon survey (CMS) (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000) in 1994 asked R&D managers of U.S. firms[2] about the effectiveness of several appropriability mechanisms. Surprisingly, both surveys found that non-patent mechanisms such as lead time, secrecy, and complementary capabilities are at least as important as patents. Also, both surveys found that the appropriability mechanism's effectiveness varies significantly across industries. Surveys conducted in Switzerland (Harabi, 1995), Japan (Cohen et al., 2002), and Finland (Hurmelinna-Laukkanen and Puumalainen, 2007) also resulted in a similar conclusion. The Finnish survey claimed that appropriability of innovation should depend on contractual and employee relationships as well as patents, secrecy, or lead time. By examining the relationship between appropriability and imitativeness, the researchers argued that human factors are important to appropriability because knowledge and information can flow to competitors through communications and employee mobility. This broad interpretation of appropriability implies that appropriability conditions are not just subject to technology- or industry-specific factors but also to those factors at the firm or invention level. The Finnish survey also found that the effectiveness of patents was ranked only behind lead time, secrecy, learning curve, and contract strength. In sum, the relative effectiveness of patents in appropriating benefits from invention and protecting the competitive advantage is evaluated lower than secrecy or lead time across type of innovation, time, and country, except for product innovation in the early period (Yale survey) and in Japan. However, we cannot say that patents are not important in appropriating innovation. Indeed, the perceived importance of patents has increased

[2] Firms included in both surveys are limited to R&D-performing firms, and the samples are biased toward large firms. The Yale survey collected responses from 130 publicly traded firms. The CMS collected responses from 1,478 R&D labs.

during the last few decades. In a survey conducted by the Business and Industry Advisory Committee to the OECD (BIAC)[3] in 2003, 67% of respondents answered that the average value of patents had increased over the past ten years (Sheehan, Martinez, and Guellec, 2003). In the same survey, 89% of respondents reported that the risks of not patenting had also increased over the past ten years. The recent surge in the number of patents and patent propensity supports this observation (Hall and Ziedonis, 2001; Kortum and Lerner, 1999; van Zeebroeck et al., 2008). The rankings of the effectiveness of each appropriability mechanism from these surveys are summarized in Table 2.1.

.

[3] The respondents to the BIAC survey are 105 firms from Europe, North Americas, and Japan. About 80% of responses came from firms with 1,000 or more employees or with R&D budgets above USD 10 million. We could not find methodological descriptions of this survey, so we cannot say whether this survey is representative or not. This survey is only indicative.

Table 2.1 Effectiveness of appropriability mechanisms (rank)

Appropriability mechanisms		Yale survey in 1983	Swiss survey in 1988	CIS in 1993	CM survey (U.S.) in 1994	CM survey (Japan) in 1994	Finnish survey in 2004
		Product, process	Product, process	Product, process	Product, process	Product, process	Product
Patents	To prevent duplication	4, 5	6, 6				
	To secure license income	5, 6	4, 5	4, 4	5, 5	2, 4	5 (IPR)
Secrecy		6, 4	4, 4	2, 3	2, 1	5, 2	2
Lead time		2, 1	2, 1	1, 1	1, 3	1, 3	1
Complementary sales/svc		1, 3	1, 2	-	4, 4	4, 5	-
Complementary manufacturing		-	-	-	3, 2	3, 1	-
Learning curve		3, 2	3, 3	-	-	-	3 (tacitness)
Complexity of product design		-	-	3, 2	-	-	-
Contracts/ other legal		-	-	-	6, 6	-	4
HRM		-	-	-	-	-	7
Labor legislation		-	-	-	-	-	6

Yale survey (Levin et al., 1987): 650 responses from 130 lines of businesses
Swiss survey (Harabi, 1995): 358 responses from 127 lines of businesses from R&D performing firms
CIS survey in 1993 (Arundel, 2001): 2849 R&D-performing firms in Norway, Germany, Luxembourg, the Netherlands, Belgium, Denmark, and Ireland
CM survey (Cohen et al., 2002): 1478 U.S. firms. 643 Japanese firms
Finnish survey (Hurmelinna-Laukkanen and Puumalainen, 2007): 299 Finnish firms. Patents include other IPRs. HRM includes restrictions on employee mobility and communication. Labor legislation includes employment contracts and employee non-competes.

Patents, although recognized generally as ineffective means of protecting invention across all of these surveys, seem to be effective in some industries. Also, the protective effectiveness of patents for product technology is different from process technology. In

the Swiss survey, the process patents were rated low in protective effectiveness in all industries. However, the product patents were rated higher than secrecy (but still lower than lead time, complementary sales, and learning curve/cost advantage) in the machinery and metal processing industry and the chemicals industry. According to the Carnegie Mellon survey for the U.S. firms (Cohen, Nelson, and Walsh, 2000), drugs, electrical equipment, basic chemicals, and medical equipment industries are relatively highly ranked in the effectiveness of patents. Industries in which patent is not an effective means of appropriability include food, textiles, and printing.

In this section, we briefly reviewed various appropriability mechanisms identified in the literature. In sum, the literature finds that appropriability of an invention depends not only on the legal institution, but also on other factors such as competitive environments, internal capability of a firm, and appropriability strategy.

2.2.2. Commercial use of patented inventions

According to the literature, about half or more patents are put into commercial use. One study conducted during the late 1950s reports that the rate of use of the U.S. patents issued in 1938, 1948 and 1952 was 49.3% at the time of the survey (Sanders, Rossman, and Harris, 1958).[4] However, this rate is much lower than that of recent European patents. The PatVal-EU reports that about 63.9% of European patents filed between 1993 and 1997 inclusive had been used by the time of survey, 2002-2003 (Giuri et al., 2007).

[4] The rate including expected use during the full lifetime of a patent calculated by Sanders, Rossman, and Harris is about 57.2%.

Recently, more detailed information about reasons to patent had been reported through surveys conducted in the United States, Japan, Switzerland, and Germany. The rank order of importance of each reason is summarized in Table 2.2. Two common findings across the surveys are worth mentioning here. First, commercial exploitation is ranked in the highest position across all surveys. Second, even the patents not intended for commercial uses may generate value to the patentees. Such uses include blocking competitors, reducing litigation risks, and enabling entry into new/foreign markets. The first two reasons are highly ranked in the U.S. and Japan, while the entry motive is highly ranked the German survey.

Licensing or cross-licensing is reportedly important in Swiss and OECD surveys but not important in the U.S., Japan, and German surveys. Industry heterogeneity is also mixed. Cohen et al. (Cohen, Nelson, and Walsh, 2000) found that there is a clear discrepancy in motives for patenting between "complex" industry and "discrete" industry. In the German survey, motives for patenting were not different across sectors except for exchange motives between the biotech industry and other industries (Blind et al., 2006).

Table 2.2 Reasons to patent (rank)

	Swiss (Harabi, 1995)	OECD (Sheehan, Martinez, and Guellec, 2003)	CMS U.S. in 1994 (Cohen et al., 2002)	CMS Japan in 1994 (Cohen et al., 2002)	German survey in 2002* (Blind et al., 2006)
	Product, process	Aggregate	Product, process	Product, process	Aggregate
Commercial exploitation/ preventing duplication	2, 1	1	1, 1	1, 2	1
Licensing	1, 1	3	6, 6	5, 5	8
Cross-licensing/ to improve bargaining positions	2, 3	2	4, 4	4, 4	6
Blocking competitors (w/o primary purpose for own use)	5, 5	NA	2, 2	2, 1	5
Preventing inventing-around other key patents	NA	NA	NA	NA	3
Preventing suits	NA	NA	3, 3	3, 3	3
Employee evaluation/ inventor reputation	6, 6	NA	7, 7	6, 6	7
For entry into foreign/new markets	4, 4	4	NA	NA	2
Firm's reputation	NA	5	5, 5	7, 7	4

German survey (Blind et al., 2006): 522 firms which had filed at least three patents at the EPO in 1999. The German survey asked 15 detailed motives including all of the above motives plus the motives related to securing regional markets and firm values. Then they grouped them into 5 categories according to factor analysis. We only ranked the motives listed in the above table and skipped those not listed here by aggregating them into higher-ranked motive in the same cluster. Also, Blind et al. regard defensive blocking as a concept covering both preventing inventing-around and preventing legal suits to guarantee room for technological maneuvering.

2.2.3. Market for Technology

The presence of a market for technology facilitates technology transfer and enhances the division of innovation labor. Most empirical literature on the market for technology examines the determinants of (cross-) licensing or determinants of particular features of licensing agreements (e.g., exclusivity or involvement of knowledge transfer). Below, we give a brief review of the empirical studies on the determinants of licensing. A detail review on each study is provided in Appendix Table A. 1.

The effective protection of intellectual property rights are reported as an important mechanism to promote licensing. Gans, Hsu and Stern (2006) found that projects resulting in patent, especially granted patent, are more likely to reach to licensing agreements. Nagaoka and Kwon (2006) found that patent-mediated cross-licensing deals are more likely to occur in Japanese firm than deals involving only know-how transfer. Patent effectiveness as being measured as either a perceived strength (Arora and Ceccagnoli, 2006) or industry-level patent propensity (Kim and Vonortas, 2006) is also reported as a strong driver of licensing.

There is robust industry heterogeneity in licensing propensity. Analyzing 1,612 licensing contracts in the early 1990s, Anand and Khanna (2000) found that chemical, computer, and electronics industries are prominent in licensing. They pointed out heterogeneity of appropriability regime as a source of industry heterogeneity. Arora, Fosfuri, and Gambardella (Arora, 1997; Arora, Fosfuri, and Gambardella, 2002; Fosfuri, 2004)

attempted to explain industry heterogeneity in a more stylized way. After conducting a detailed historical case study of the chemical industry, they concluded that industry structures (such as emergence of specialized engineering firms, market share of licensors, and degree of product differentiation) had affected the licensing propensity. They pointed out two fundamental factors driving this phenomenon: revenue earned from licensing and rent dissipation caused by licensing. According to their arguments, the development of a market for technology depends on the strategic behavior of industry participants as well as on evolutionary paths of the industry

Various firm capabilities also influence licensing propensity. They include prior experience (Kim and Vonortas, 2006), the size of the firm (Gambardella, Giuri, and Luzzi, 2007; Nagaoka and Kwon, 2006), and the presence of alternative commercialization channels, such as marketing and sales (Kollmer and Dowling, 2004) or complementary assets (Gans, Hsu, and Stern, 2002). One common finding is that firms lacking some assets required for commercialization (e.g., small firms, start-ups, or partially integrated or non-integrated firms) are more likely to license.

2.3. Schumpeterian Legacy on Innovation

A firm is an important social entity that transforms ideas into innovation. This section reviews a portion of the literature dealing with questions about two important aspects relating innovation. First, who innovates? This question has drawn continuous academic

attention ever since Schumpeter's emphasis on entrepreneurship (Schumpeter, 1939, 1942). The research frontier of this theme recently shifted from the simple small-large dichotomy in firm size to a more complex characterization. These characteristics involve, among others, the competitive environment to which a firm belongs, presence and effectiveness of a market for innovative knowledge, technology and knowledge stock available to the firm, and strategic intentions of the firm. Under the rational behavioral assumption of a firm, the firm will respond differently to the innovation needs it has determined depending on these factors. Hence, to better understand who innovates, we have to understand why firms innovate. This comprises the second question of this section. A natural question that may well follow those about who innovates and why would be how do they innovate. The literature dealing with this question will be reviewed in the next section of innovation processes.

In *Capitalism, Socialism and Democracy* (1942), Schumpeter emphasizes the role of monopolization in innovation. A monopoly, more loosely defined as a large firm, has a discriminating role in both the preconditions and aftermath of innovation. As a precondition, Schumpeter points out the relative advantage of a large firm in "the sphere of influence of the better [good]" (Schumpeter, 1942, p. 101) and good financial standings. As a result of innovation, a firm will enjoy a transient monopoly state caused by imitation lag. Therefore, in this Schumpeterian world, "perfect competition is and always has been suspended whenever anything new is being introduced" (p. 105). This Schumpeterian hypothesis urged researchers to look at the relationship between market structure (depending on firm size) and technological progress.

The Schumpeterian hypothesis was extensively tested during the 1960s through the 1980s. As neatly summarized by Cohen and Klepper (1996b), these studies consistently found that R&D investments increase with firm size, although not disproportionately, but that innovation output, mostly measured using patent counts, decreases disproportionately as the level of R&D or firm size increases. The arguments underlying the assumption that a large firm innovates more than a smaller one consider aspects of both demand and supply. First, a larger firm has a smaller unit cost of R&D ("cost-spreading effect") than its smaller counterpart (Cohen and Klepper, 1996a, 1996b). On the supply side, a larger firm will have more lump-sum funds to invest in R&D. More R&D will diversify the research portfolio and spread R&D risks into several parallel projects to raise the odds of success. A larger investment in R&D constitutes a larger R&D team, which is composed of supposedly better specialized personnel or which better divides the R&D labor force. As a consequence of this scale economy of R&D investment, a firm investing more in R&D will have advantages in its research portfolio, R&D risk-spreading, efficiency of R&D teams, and absorptive capacity. Besides R&D diversity/specialization, a larger firm enjoys an operational advantage through better vertical integration and specialization (Teece, 1986). However, although the above arguments explain the increasing R&D expenditure as the firm size grows, it does not explain why it grows disproportionately.

Table 2.3 Literature about R&D expenditure, innovation, and firm size

Category	Relationship with firm size	Studies	Remark
R&D expenditure	Proportional	(Scherer, 1965) up to a certain level	Fortune 500 firms
	Disproportionately more	(Soete, 1979) in some industries in the U.S.	Firms with >25k
	Disproportionately less	(Mansfield, 1964) except for chemicals	
R&D productivity	negative	(Mansfield, 1964) innovation/R&D	
	negative	(Link and Rees, 1990) Total Factor Productivity	Major user industry of univ research
	U-type	(Tsai, 2005; Tsai and Wang, 2005) TFP	Taiwanese firms
Innovation	mixed	(Acs and Audretsch, 1987) depending on industries	

Table 2.4 Literature on firm size and performance, governance mode and the nature of innovation

Author	Industry	Data/ Technique	Variables of interests	Variable Examined	Effect
(Veugelers and Cassiman, 1999)	Manufact-uring (Belgium)	Cross section: logit	A firm does innovation (=1)	Small firms (<50 employees)	-***
				Large firms (>500 employees)	+***
(Veugelers and Cassiman, 1999)	Manufact-uring (Belgium)	Cross section: multi-nomial logit	make only, buy only, make and buy (of upstream innovation resources)	Small firms (<50 employees)	+** +*** -**
				Large firms (>500 employees)	-** - +**
(Tushman and Anderson, 1986)	Cement, airlines, and mini-computers	Cross section/ Fisher's exact test	Competence-enhancing	New firms < Existing firms	*
			Competence-destroying	New firms > Existing firms	*

Note: the signs denote the direction of effects of "variables examined" on the "variables of interests." Asterisks denote statistical significance of the effects (* denotes a 10%

significance level, ** denotes a 5% significance level, *** denotes a 1% significance level).

The Schumpeterian hypothesis, which was not articulated by Schumpeter himself but named by his disciples, actually refers to two closely linked but different factors: firm size and market structure. Schumpeter(1942, p. 101) explicitly claimed that the "mere size [of a firm] is neither necessary nor sufficient." Although he mentioned a supply condition—advantageous financial standings of a larger firm—he seemed to "have almost certainly appropriability mechanisms in mind" (Nelson and Winter, 1982), in which oligopolistic market conditions play a key role. Empirical studies on the market concentration and the rate of innovation followed. In British manufacturing firms between 1972 and 1982, Blundell et al. (1999) found that a less concentrated industry generated a higher level of aggregate innovation as measured with the direct count of innovations. At the firm level, they found that high-market-share firms were more likely to commercialize innovations within industries. Using the sample composed of firms listed in the London Stock Exchange, Aghion et al. (2005) also found similar results. In their analysis, market competition as measured in the price-cost margin averaged by industry was significantly associated with citation-weighted patent counts and revealed an inverted-U relationship. What they argued as the underlying force driving this phenomenon was the balance between the incentives for incremental profit generation through innovation under competition and the disincentives for laggards to conduct innovative research when there is severe competition.

2.4. Teecian Arguments on the Profitability of Innovation

The huge volume of literature that has tested the Schumpeterian hypotheses does not converge on any undisputable conclusion. One reason for this inconclusiveness might be that aggregate units, such as the firm or industry, could not effectively capture the complex and heterogeneous activities of innovations carried out across firms and industries. Firm size alone, for example, cannot appropriately capture the heterogeneous innovation activities performed by two different firms of the same size. Moreover, innovative capability and activities of contemporary firms are not necessarily bounded by firm or industry boundary but are linked to outer capabilities by research collaboration, strategic alliances, or technology licensing. Therefore, we need to unpack what is going on within firms in order to better understand innovation.

Teece (1986), among others, developed a quite useful framework to analyze the mechanisms by which firms commercialize their inventions. In order to explain why many innovators fail to make a profit from innovation, he presents a simple model composed of three actors—innovator, follower/imitator, and owners of co-specialized assets[5]—and two alternative strategies of the innovator: integrate or contract out.[6] In this zero-sum type of game, he then argues that a choice of strategy conditioned on three key factors should determine to whom (innovator or follower) the profit from innovation

[5] He stated that "[i]f there are innovators who lose there must be followers/imitators who win" (Teece, 1986, p. 286).
[6] In a later revision (Teece, 2006), Teece partially addressed an intermediate strategy: strategic alliances.

accrues. The three conditioning factors are the dominant design paradigm of technology, regimes of appropriability, and complementary assets. The latter two building blocks are especially applied to lots of business strategy and innovation research and have proved their explanatory power to some extent. The Teecian framework is especially relevant to this work in that it directly attempts to explain the reasons why the innovator selects a particular strategy between two alternatives—internal and external commercialization. The Teecian framework was further refined by Gans and Stern (2003) and applied to the context of new technology-based entrepreneurs. In this section, we briefly introduce the three building blocks and decision frameworks and discuss their strengths and weaknesses.

2.4.1. Dominant Design Paradigm

Seemingly affected by Kuhn's explanation of scientific revolution (Kuhn, 1970) and incorporating evolutionary explanations of technological progress (Abernathy and Utterback, 1978; Dosi, 1982), Teece argued that the strategy of a firm facing a technological innovation should differ by the degree of dominance of the technology in the market. In the pre-paradigmatic stage, the strategic priority of an innovator is set to aligning the new technology with the market needs and surviving through "considerable trial and error in the marketplace" (p. 288). As the market selects a dominant design, uncertainty in the validity of technology is removed, and competition shifts from product innovation to process innovation (Abernathy and Utterback, 1978). Therefore, strategic importance shifts to the "scale and learning" by which a firm can build lower-unit-cost

production and distribution capabilities. Complementary assets play a critical role in this stage. In Teece's original article, the design paradigm is recognized as exogenous, but in a later article (Teece, 2006), Teece points out some endogenous elements contributing to setting a standard as indicated by research about industry standards (Arthur, 1990; David, 1985; Katz and Shapiro, 1994). The Teecian framework does not intend to explain technological evolution nor how an emerging technology becomes a dominant design. Teece's contribution is in linking managerial choices to a configuration of the regime of appropriability and relative positions in complementary assets, given a paradigmatic technology. He also argues that his framework gives an implication about the timing of market entry depending on those two conditions (Teece, 2006). However, as shown in an extensive review on the relevant literature by Murmann and Frenken (2006), dominant design concept is not only valid and widely adopted, but also affects the nature of competition and the innovative behavior of firms.

2.4.2. The Regime of Appropriability

According to Teece (1986), a regime of appropriability "refers to the environmental factors, excluding firm and market structure, that govern an innovator's ability to capture the profits generated by an innovation" (p. 287). In Teecian terms, these factors are related to the degree of ease with which an innovation can be imitated by the competitors. What Teece points out as factors affecting the imitability of an innovation are the nature of technology (especially the degree of tacit knowledge) and legal environment (such as effectiveness of intellectual property protection) surrounding the technology. As

summarized here, the Teecian appropriability condition is exogenous by definition. By separating out environmental conditions from firm and market factors, Teece shows why and how the ownership of, and a relative position in, complementary assets matters in appropriating innovation. However, as increasingly observed, firms in some industries take on appropriability conditions by exerting deliberate IP strategies.[7] Therefore, appropriability regime might be determined endogenously in some industries. In the later part of this paper we will argue that, in some complex product industries where technological components composing a final product are highly interdependent, a certain coordinated patent strategy of a group of key technology players may change the appropriability conditions of the industry.

2.4.3. Complementary Assets

Probably the most important contribution of Teece's 1986 paper is to put the concept of complementary assets, then a novel construct, out on the table of innovation discussions. Complementary assets are "other capabilities or assets" that a "core technological know-how in innovation" requires for its successful commercialization (p. 288). They include various services, such as manufacturing, distribution channels, complementary technologies, and so on. Teece classified complementary assets according to their relationship with innovation. Generic assets have small mutual dependence with an innovation. Some assets are specialized to an innovation with either unilateral or bilateral

[7] See two examples discussed by Pisano (2006) in which strong downstream complementary asset owners, one in pharmaceuticals and the other in computer hardware, took strategic actions toward loosening the upstream appropriability regime by putting human gene sequence data in the public domain and by supporting open source software, respectively.

dependence between them. What matters in commercialization decisions of a firm is either specialized (unilateral dependence between assets and innovation) or co-specialized complementary assets, because the owners of the latter type of assets may behave opportunistically and hold up the innovator to appropriate more from the commercialization of innovation.

2.4.4. Channel Strategy: Integration vs. Contract

Given the configuration of three elements (i.e., the status of the invented technology in the technology-market space, the regime of appropriability, and the structure of complementary assets), the Teecian innovator chooses the more profitable strategy between two organizational alternatives: internalize or contract.[8] The basic decision rule is, "if in doubt, outsource" (Teece, 2006, p. 1140). Under this decision rule, given a tight appropriate regime, the Teecian innovator does not have any reason to integrate complementary assets because he can reap the commercialization profit from a contract regardless of its relative asset positions to the owners of complementary assets. Teece's decision framework sheds light on weak appropriability regimes. Simply put, the Teecian innovator internalizes a commercialization process only if the following conditions are met: 1) critical complementary assets are available in-house; 2) they are specialized; 3) the cash position makes it feasible to build them in-house; 4) the innovator is *not* disadvantageously positioned in commissioning complementary assets compared to imitators or competitors; and, finally, 5) the innovator commands a weaker market power

[8] The later update (Teece, 2006) adds an intermediate choice, strategic alliance, in between these two extreme choices.

than independent owners of complementary assets. The decision flow is shown in Figure 2.1.

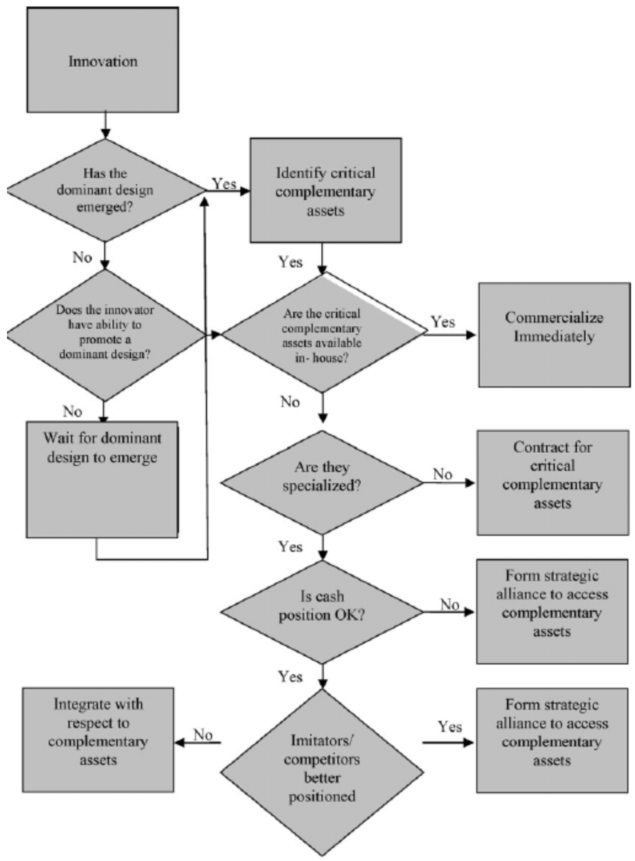

Figure 2.1 Teecian market entry strategies under weak appropriability regimes (Fig. 3 in Teece, 2006)

2.4.5. Discussions

Teece's framework sheds light on the relationships between firm strategy and innovation and provides essential building blocks for its theoretical understanding. However, progress in the theoretical and empirical research on firms and innovation during the last two decades reveals some shortcomings and weaknesses of the framework. In this section we briefly review the empirical research relevant to the Teecian framework and then discuss several points for improving the framework.[9]

Empirical research on commercialization strategy and appropriability regime

One prominent mode of contracting for commercialization is licensing. Teecian decision framework implies that licensing propensity should be higher in a tight appropriability regime than in a loose one because licensing decision in a tight regime will be less constrained by complementary asset conditions. Grindley and Teece (1997) claimed that the U.S. policy shift toward strengthening IP and lifting up antitrust regulations that had distorted the value of IP must force firms in electronics and semiconductor industries to develop patentable technology or to license it. Anand and Khanna's (2000) research on strategic alliances of U.S. firms showed that the propensity of licensing deals (relative to all the other forms of alliance agreements) is significantly different across industries (higher propensity and stricter exclusivity in the drug and chemical industry and vice versa in the computer and electronics industry). They argued that the heterogeneity of the

[9] Some refining points are discussed by Teece himself in his recent reflection (Teece, 2006).

strength of IP (strong IP in drug/chemical and weak IP in computer/electronics) explains the heterogeneity in both propensity and features of licensing deals across industries.[10] Kim and Vonortas (2006) also found similar results using the patent intensity (the number of patents per R&D expenditure) of industry.

Commercialization strategy also depends on a firm's appropriation strategy. Formal grant of intellectual property rights increases the licensing propensity of start-up firms (Gans, Hsu, and Stern, 2002, 2006). Gambardella et al. (Gambardella, Giuri, and Luzzi, 2007) argued that patent breadth (as measured either by the number of claims or the number of different technology classes) may be a proxy for the strength of patents (broader patent, harder to imitate) and found that both measures are positively associated with the likelihood of willingness to license in European firms. Arora and Ceccagnoli (2006) found from a cross-industry survey answered by 757 R&D managers of U.S. firms that the patent effectiveness perceived by an individual firm (as evaluated by R&D managers) is positively associated with the licensing propensity, but only when the firm lacks the complementary assets.

These empirical studies cast one important point about appropriability arguments. In the Teecian explanation, appropriability is exogenously determined by the legal environment of intellectual property rights and the nature of technology relevant to inherent imitability. However, the licensing literature provides some evidence that appropriability strategy at the firm level and patent level also affects the commercialization strategy of a firm.

[10] Note that Anand and Khanna (2000) do not compare "integrate" with "contract" but "licensing contract" with all the other types of identified alliances, such as joint venture, marketing agreements, or R&D agreements.

Furthermore, several large-scale industry surveys (Blind et al., 2006; Cohen, Nelson, and Walsh, 2000; Levin et al., 1987; OECD, 2003) consistently show that a variety of appropriability mechanisms other than patents (such as lead time, secrecy, or complementary technology) are widely adopted among firms. Gans and Stern (2003) make the shrewd point that it is not the level but the type of appropriability that drives the commercialization strategy of start-up firms. Therefore, in order for us to better understand the commercialization of innovation, a simplified view of appropriability regime as submitted by Teece needs to be revised to address a sub-regime variety and different types of appropriability strategy exploited by firms. We will discuss this issue below.

Empirical research on commercialization strategy and complementary assets

Two broad research streams—strategic alliances literature and licensing literature—test the empirical validity of complementary assets in explaining a firm's commercialization strategy.

In conclusion, although the Teecian framework opens up a new avenue to research about innovation and commercialization, it is far from comprehensive. Also, considering the significant progress made in the discussions of the commercialization of innovation, the patenting behavior of firms, and firm boundaries since 1986, efforts to integrate these novel theoretical and empirical perspectives into the Teecian framework will further our understanding of this matter as well as enrich the framework itself. We will discuss three points of improvement.

First, appropriability concept should address endogeneity of appropriability (Jacobides and Winter, 2005; Pisano, 2006) and diverse appropriability mechanisms widely adopted among contemporary firms. When this expanded conceptualization of appropriability successfully fits into the Teecian framework, it will provide a useful starting point for us to explain strategic non-use of patents. We approach this issue by synthesizing the cumulative research results in transaction cost economics into the Teecian framework.

Secondly, the Teecian argument about complementary assets is based on two elements: the possibility of opportunistic behavior by the owner of a specialized asset (the "hold-up" problem) and the relative advantage of the innovator in commissioning complementary assets. The former is a main point of TCE. The latter, albeit not rigorously articulated in Teece's framework, can be enriched through knowledge-based (Conner and Prahalad, 1996; Kogut and Zander, 1992; Nonaka, Toyama, and Nagata, 2000) or capability-based (Eisenhardt and Martin, 2000; Teece, Pisano, and Shuen, 1997) views of firms in which internal synergy is an important factor determining market or hierarchy.

Thirdly, knowledge networks and open innovation perspectives should be integrated with Teecian arguments. The knowledge network literature claims that contemporary innovation activities dispense with the networked relationships with various external entities (Powell, Koput, and Smith-Doerr, 1996). Also, the strategic alliance literature observes that experiential relationships between firms importantly affect the forms and types of alliances. We will argue that knowledge-flows and collaboration networks

during the invention process should affect the commercialization strategy of the resultant invention.

Finally, in some complex technologies, complementary technology works as a crucial bottleneck (or enabler) for a firm to successfully introduce its innovation to the market. Even an incremental innovation in the related technology area may become a life-and-death matter for a firm in some complex technology or network goods industry (Kash and Kingston, 2001) and, thus, an innovator's strategy to enable timely sourcing of those bottleneck technologies is critical. As technologies become more interdependent and systemic, the importance of complementary technologies in the success of innovation also increases (Somaya and Teece, 2001; Teece, 2006). Teece (2006) later admits that, in his 1986 article, this important aspect was considered as a part of complementary assets and relatively overlooked by focusing on the enterprise level value chains (p. 1,139). We argue that the owner or innovator of complementary technology deserves to be the fourth actor on the innovation commercialization playing field. By explicitly considering the roles and strategies of innovators to deal with complementary technologies, we expect that we can explain some important aspects of strategic uses of patents.

2.5. Economics of a Firm's Make-Buy Decision

Although Teece did not cite any research from transaction cost economics in his 1986 article, his arguments resemble the discussions in economics of contracts, especially

transaction cost economics and property rights theory. Both transaction cost economics (henceforth "TCE") and property rights theory (henceforth "PRT") have their roots in Ronald Coase's conceptualization of transaction costs in his article *The Nature of the Firm*, published in 1937. TCE and PRT both hinge on contractual incompleteness and appropriable ex post quasi rents stemming from relation-specific investments. However, as Williamson pointed out (Williamson, 1985, 2002), while the former focuses on the opportunistic behavior that may occur in the implementation stage of a contract, the latter focuses on ex ante incentive alignments. Although both TCE and PRT have evolved from common antecedents, this difference makes sometimes divergent empirical predictions (Lafontaine and Slade, 2007; Whinston, 2003). In this section, we will briefly review the skeleton of each theory, bearing in mind how they can enrich or modify Teece's framework. Note that theoretical development and empirical tests for both theories have been conducted mostly in the backward integration context[11]—e.g., cases such as when a manufacturer decides whether to integrate supplier capacity (Lafontaine and Slade, 2007)—while the main focus of this study is the decision situation where the owner of upstream assets (i.e. R&D and invention) decides whether to integrate necessary downstream assets, such as manufacturing or marketing capacity. The applications of TCE to the forward integration cases have been recently conducted by researchers looking at the market for technology.

[11] One branch of the economics of contracts looking at forward integration is Agency theory, which centers around incentive matching between a principal and an agent and the moral hazard of the agent. Although this stream of research may shed light on this study, we will not give much attention to this theory because we do not have any empirical instruments to test the agent's relation-specific behavior.

In the original conceptualization by Ronald Coase, transaction cost is defined as "a cost using the price mechanism" (Coase, 1937, p. 390). While this definition implies that transaction costs arise from market transactions, some recent transaction-cost economists such as Oliver Williamson use transaction costs broadly to refer to the governance costs that arise either within firms or across markets. Kenneth Arrow views transaction costs as costs "attached to any market and indeed to *any mode of resource allocation*" (emphasis added; Arrow, 1969). Similarly, Williamson analogizes transaction costs to friction in the physical world and regards them as the "costs of planning, adapting, and monitoring task completion under *alternative governance structures*" (emphasis added; Williamson, 1981, pp. 552-553).

TCE assumes the bounded rationality of human beings and the impossibility of writing a complete contract ex ante. In this incomplete world of contracts, contracting parties (e.g., manufacturer and supplier) have incentives to behave opportunistically to appropriate more of the quasi-rents generated from the contract relationship but not fully specified ex ante in the contract. A typical form of this ex post opportunistic behavior is "hold-up" as emphasized in the TCE literature. Therefore, in the situation where the manufacturer expects high chances of hold-up by suppliers, it would choose to integrate supplier capacity under its authoritative control, which reduces opportunistic behavior and saves transaction costs if production costs of alternative organizational forms are equal. TCE literature contends that asset specificity, uncertainty, and complexity should be closely related with the ex post opportunistic behavior (Klein, Crawford, and Alchian, 1978; Williamson, 1991). Asset specificity refers to "the degree to which an asset can be

redeployed to alternative uses and by alternative users without sacrifice of productive value" (Williamson, 1991, p. 281). Williamson identifies six types of asset specificity: 1) site specificity, which refers to the advantage of two or more assets jointly located to each other; 2) physical asset specificity, which refers to physical equipment customized to each other; 3) human asset specificity, which refers to training and learning by doing; 4) brand name capital; 5) dedicated assets, which are "discrete investments in general purpose plant that are made at the behest of a particular customer"; and 6) temporal specificity.

Empirical tests of TCE gravitated around the relationship between asset specificity and the tendency of vertical integration in sourcing intermediate product markets. A recent survey of the empirical literature by Lafontaine and Slade (2007) shows that the propensity of vertical integration is indeed positively associated with various types of asset specificity as predicted by TCE. In addition to the asset specificity, their survey shows that complexity and uncertainty, which hinder contractors from writing a complete contract ex ante, are also positively associated with the propensity of vertical integration.

In the innovation context, while a huge volume of literature in the strategic alliance tests the impact of transaction costs on the governance structure of alliance agreements, only a few studies examine how TCE predictions affect vertical integration of innovation outputs. The licensing research examines the rate of licensing, a less hierarchical mode of innovation commercialization, in relation with transaction cost variables such as the strength of patents or the ownership of complementary assets. However, it does not

directly test the market versus hierarchy because the counterpart of licensing tested in the literature usually include non-licensed inventions, which may include non-used ones as well as internally commercialized ones. Key studies are summarized in the following tables. As predicted by TCE, as asset specificity, uncertainty, and complexity increase, more hierarchical governance structure is chosen in alliance, R&D procurement, or invention commercialization. In the innovation context, many studies test the effect of the strength of appropriability regime on the governance structure instead of separately testing the effect of elements comprising appropriability hazards. Aside from Oxley's test of geographic uncertainty, Veugelers and Cassiman's test based on the Belgian Community Innovation Survey show the opposite direction as predicted by TCE—i.e., the lower uncertainty or lower appropriability hazard is related to a more hierarchical structure ("make" rather than "buy"). This observation is better explained using property rights theory.

Table 2.5 Literature about effects of asset specificity on the choice of governance structure

Author (Year)	Industry	Data/ Technique	Governance structure tested	Variable Examined	Effect on HI
Pisano (1990)	Pharmaceutical firms	Cross section: Probit	R&D contract vs. backward integration (=1)	The number of R&D suppliers	-*
Gulati and Singh (1998)	Biopharma, new materials, and automobile	Pooled cross section: logit	Alliances (contractual -> minority equity investments -> joint ventures)	Types of organizational interdependence	+*

Table 2.6 Literature about effects of complexity on the choice of hierarchical governance structure

Author (Year)	Industry	Data/ Technique	Governance structure tested	Variable Examined	Effect on HI
Gulati and Singh (1998)	biopharmaceutical, new materials, and automobile	Pooled cross section: logit	Alliances (contractual -> minority equity investments -> joint ventures)	R&D alliances (vs. non-R&D)	+*
Oxley (1997)	General	Cross section: Ordered probit	Alliances (unilateral-> bilateral -> equity-based)	Design activities Mixed activities Multiple products or technologies	+* +* +*

Table 2.7 Literature about effect of uncertainty or appropriability regime on the choice of hierarchical governance structure

Author (Year)	Industry	Data/ Technique	Governance structure tested	Variable Examined	Effect on HI
Oxley (1997)	General	Cross section: Ordered probit	Alliances (unilateral-> bilateral -> equity-based)	Wider geographic area The number of firms	-* +*
Gulati and Singh (1998)	Biopharma-ceuticals, new materials, and automobile	Pooled cross section: logit	Alliances (contractual -> equity investments -> joint ventures)	Weaker appr. Regime (new materials and automobile)	+*
Oxley (1999)	General	Cross section: logit	Alliances (contractual -> equity joint ventures)	National appropriability regime of the host country	-***
Veugelers and Cassiman (1999)	Manufacturing	Cross section: multi-nomial logit	Of upstream innovation resources, make only buy only make and buy	Beliefs of the firm about any protective mechanism (legal, secrecy, lead time, etc.)	+ -*** +
Anand and Khanna (2000)	General	Cross section: ML	Licensing partners (unrelated -> related)	Weaker appr. Regime (computer/ electronics vs. bio)	+*
Gans, Hsu, and Stern (2002)	General (SBIR funded start-up)	Cross section: probit/ logit	Coop (cooperation -> self comm.=0)	# of patents (binary)	-*
Fontana, Geuna, and Matt (2006)	Food and beverage, Chemicals (w/o pharma), radio, television and communication equipment and apparatus, Telecommunication services, Computer and related activities	Cross section/ neg. binomial	Propensity to participate in R&D collaboration with universities or PROs	Use patents to protect innovation	+**

2.6. Resources, Capabilities, and Complementary Assets

Teece's arguments about complementary assets hinge on two dimensions of complementary assets. The first dimension is whether an invented technology requires complementary assets and, if so, how specialized they are. The implication for the choice of governance structure stemming from this dimension is similar to the asset specificity arguments in TCE. The second dimension is the competitive position of the inventor in sourcing the complementary assets compared with, first, its competitor, and second, the independent owner of the assets. Teece argued that an inventor who is weakly positioned in commissioning (contracting) the complementary assets compared to an imitator (the asset owner) should prefer integration to contract. About this dimension, TCE gives a partial prediction consistent with Teece's prediction. A weak position of the inventor in commissioning the complementary assets will increase contractual uncertainty and, thus, increase the transaction costs. Although the latter may be better explained in the incentive theory, considering the way that different marginal returns on the investment affect the choice of governance structure, Teece's arguments are largely parallel to TCE arguments.

However, both arguments overlook one critical aspect. While both theories focus on whether there will be positive transaction costs as a key element of decision-making, they largely ignore the effects of potential synergy that may be additionally produced by integration. As an example, think about tight internal collaboration between a technology development group and a manufacturing division. Among others, assume that this

relationship bears a higher degree of human asset specificity. A general prediction of TCE is that internal procurement is preferred for the assets having a higher degree of human asset specificity because authoritative control and internal monitoring are more effective than a contractual relationship. Assuming zero internal transaction costs, the innovator will choose integration when he forecasts positive transaction costs across markets. But this is only a partial view. There is a case in which an innovator chooses integration even under the zero transaction costs across markets and, thus, betrays a basic assumption of Teece's decision rule: "if in doubt, then outsource." The preparation of complementary assets required for commercializing an invention and collaboration among internal organizational units are usually accompanied with employee training and learning effects, which can lead to enhanced absorptive capacity of a firm. Therefore, when an inventor expects such internal synergistic effects, he will integrate the complementary assets even if market transaction costs are minimal. This point is the core idea of a knowledge-based view of a firm (Conner and Prahalad, 1996; Kogut and Zander, 1992).

Based on the surveys of innovating firms in Sweden, Kogut and Zander (2003) found that as the complexity of knowledge increases, the likelihood to integrate such knowledge also increased. In the pharmaceutical industry, Nerkar and Roberts (2004) found that the innovative performance of firms (as measured by sales ratios of innovative products) is positively associated with firms' technology capabilities (as measured by patent stocks) in the same technology area but not with technology capabilities of distant areas (Table A. 2).

2.7. Knowledge Flows, Networks, and Open Innovation

In the previous sections, we discussed two theoretical approaches relevant to the make-or-buy decision of commercializing innovation. While TCE focuses on comparisons of the management cost with the contractual hazards in a dyadic relationship, KBV emphasizes synergistic effects that would not be produced by contractual relationships but would be possible by integrating complementary activities internally. The innovation network and organizational learning perspectives agree with KBV in that consideration of the transaction costs should be only a partial explanation of the choice of governance structure in commercializing an innovation and that some complementary combinations not attainable through market relationships should be an important dimension in determining the choice of governance structure. A critical difference from KBV, however, is found in the stretch of the boundary within which such synergistic effects happen. While KBV confines the boundary of complementary combination within a firm, the innovation network perspectives extend it over the networks of firms. Both TCE and the network perspectives focus on the relationships with external entities. However, while TCE focuses on how the attributes of the relationship work as a potential risk, the network perspectives focus on how the relationship can generate some positive benefits otherwise impossible. In this sense, we basically agree with Jacobides and Winter's contention that "TCE focuses on the conditions of exchange, to the neglect of the conditions of production" (Jacobides and Winter, 2005, p. 398). However, there is a more fundamental argument about the roles of the networks in innovation and economic behavior beyond the problem of avoidance of negatives or production of positives.

2.7.1. Embeddedness and network forms of organizations

The attacks were initiated by sociologists whose main concerns are placed in how social relations affect individual behavior. Mark Granovetter (1985) criticizes economic arguments for ignoring the social context and history of interpersonal relationships outside of which human actions cannot be formed. As a consequence, he contends that economic arguments, whether they are neoclassical or new institutional, are either *over-socialized* or *under-socialized.* In his view, networks are omnipresent (they exist even in hierarchy as well as in markets) and human actions are “embedded in concrete, ongoing systems of social relations” (p. 487).

Powell (1990) basically agrees with Granovetter on the importance of social structural embeddedness in determining economic exchanges and on the limitation of arraying economic exchanges on the market-hierarchy continuum. Nevertheless, he argues that “certain forms of exchanges are more social” (p. 300) and submits that there is empirical merit to distinguish the network form as a distinct governance structure from either market or hierarchy. Powell identifies several key distinct characteristics of each of three governance forms. The network structure is dominated by a norm of reciprocity and reputational concerns, while hierarchy (market) is dominated by administrative fiat or supervision (haggling or court enforcement). Also, information communicated over networks is richer than information obtained in the market and “freer” than that circulated in a hierarchy. Therefore, Powell contends that “[n]etworks, then, are especially useful for the exchange of commodities whose value is not easily measured” (p. 304).

According to this line of argument, a network form of organization is defined as "any collection of actors ($N \geq 2$) that pursue repeated, enduring exchange relations with one another and, at the same time, lack a legitimate organizational authority to arbitrate and resolve disputes that may arise during the exchange" (Podolny and Page, 1998, p. 59). This definition includes joint ventures, strategic alliances, franchises, research consortia, relational contracts, and outsourcing agreements.

Powell further argues that know-how, the demand for speed, and trust are critical to forming networks. The exchange of know-how, which, according to Powell, is characterized by tacitness and embodied in a highly mobile skilled labor force, is more suitable for network forms because of the lateral structure of communication and mutual obligation of networks. Dynamic adaptability of network structure, which is mostly based on the ability to disseminate and interpret information, is more suitable for the competition based on fast innovation capability. Finally, the common backgrounds that may stimulate trust among actors contribute to forming networks. In addition to these factors, needs for legitimacy and status that may be derived from network affiliation are listed as a factor affecting network formation (Podolny and Page, 1998; Stuart, Hoang, and Hybels, 1999). The key testable implications of embeddedness, therefore, are that network forms of organizations are preferred when the above-listed factors are prominent ceteris paribus and, consequently, that network forms of organizations result in unique opportunities and constraints not predicted by standard economic explanations (Uzzi, 1996). A review of empirical research testing these implications is given below.

Williamson (1991) also attempts to explain the network forms of organization ("hybrid governance structure," in his terminology) within the TCE framework. A phenomenological basis of Williamson's hybrid organizations seems to be linked to long-term contracts in which "bilateral dependency conditions are supported by a variety of specialized governance features (hostages, arbitration, take-or-pay procurement clauses, tied sales, reciprocity, regulation, etc.)" (p. 269). What is common between Williamson's hybrid organization and Powell's networks is mutual dependency, although Powell's networks are not necessarily bilateral as Williamson's hybrids are. Williamson, then, suggests five dimensions (i.e., incentive intensity, administrative controls, market adaptation, cooperative adaptation, and contract law features) that discriminate organizational forms and locates the hybrid organization around the middle of all five dimensions between two polar forms: market and hierarchy. A fundamental difference is found between Powell and Williamson. While network forms of organization are something independent from either market or hierarchy in Powell's view, hybrids are something intermediate and transient between market and hierarchy in Williamson's view. Therefore, while Powell views that network forms are suitable for fast-changing, uncertain situations based on non-price competition, Williamson claims that hybrids are not to be chosen for highly uncertain situations. In Williamson's view, equilibrium under high uncertainty can be attained through either market or hierarchy.

Empirical literature

In the section above, we show that empirical tests of embeddedness have two different focuses: 1) relationship between network forms of organizations and their outcomes and

2) effects of learning, characteristics of knowledge required for a product, the speed of demand, environmental factors for trust-building, and needs for legitimacy and status on the formation of network forms of organization. In this sense the innovation network perspectives argue that the synergistic effects should be produced over the inter-organizational knowledge networks as well as within the boundary of a firm. Powell, Koput, and Smith-Doerr (1996) claim that in high-tech industries, where knowledge is critical for a competitive advantage but broadly distributed, knowledge creation occurs not in a tightly bound and static organizational form but in a fluid and evolving community of knowledge. They state that "[a] network serves as a locus of innovation because it provides timely access to knowledge and resources that are otherwise unavailable, while also testing internal expertise and learning capabilities" (Powell, Koput, and Smith-Doerr, 1996, p. 119).

The locus of innovation, however, is not always found over the network. They cautiously confine the conditions to such industries in which knowledge is important for a competitive advantage and broadly distributed. The prominent example that satisfies these conditions is the biopharmaceutical industry; therefore, strategic alliances of the biopharmaceutical industry have been intensely studied recently.

Uzzi's study (1996) reveals interesting performance implications of network structure. While the strong ties (embedded ties rather than arm's-length ties) in the first-order network coupling have positive effects on firm survival, mixed ties in the second-order network coupling are associated with a higher survival rate. This implies the important

roles of weak ties (Granovetter, 1973) and bridges or structural holes in network performance.

Table 2.8 Literature about effects of networks on outcomes/performance

Author (Year)	Industry	Data/ Technique	Measure of outcomes	Variable Examined	Effect
(Uzzi, 1996)	Apparel	Cross section/ Logit	Firm (contractor) failure	Intensities of embedded ties	-***
				Business group affiliation (social capital)	-**
				Intensities of embedded ties of partners	U**
(Powell, Koput, and Smith-Doerr, 1996)	Biotech	Longitudinal/ panel regression	Firm growth	Degree centrality	+**
				Non-R&D network experiences	+**
			Going public	Degree centrality	+**
				Non-R&D network experiences	+**
				Collaborative R&D experience	+**
(Stuart, Hoang, and Hybels, 1999)	Biotech	Longitudinal/ hazard regression and selection OLS	The rate of and valuation at IPO	Technologically prominent exchange partners	
				Commercially prominent exchange partners	
(Afuah, 2000)	Micro-processor (RISC)	Cross section/ OLS	Log(Dollar market share)	Supplier of a new technology (RISC) was a supplier of old technology (CISC) (supplier capabilities obsolescence)	-***
				Customer capabilities obsolescence (new OS)	-***
				Backward vertical integration	-***
(Dyer and Nobeoka, 2000)	Automobile (Toyota)	Qualitative	Firm success Knowledge generation, transfer, and sharing	Supplier network	NA
(Gulati and Higgins, 2003)	Biotech	Pooled cross section/ Heckman selection	IPO success	VC partner	+**
				Underwriter prestige	+***
				Prominent downstream strategic alliances	n.s.

Table 2.8 (continued)

Author (Year)	Industry	Data/ Technique	Measure of outcomes	Variable Examined	Effect
(Rothaermel and Deeds, 2004)	Biotech	Pooled cross section/ structural equation	New products in development	Alliances for R&D	+**
			Products on market	Alliances for comer-cialization	+**
(Gulati and Sytch, 2007)	Automobile	Cross section/ 3SLS	Index of manufacturer's performance in the procurement	Joint dependence	+*
				Manufacturer's dependence advantage	-
				Supplier's dependence advantage	+
				The degree of supplier's involvement of	+**
				cooperation	+***
				Quality of information exchange	

Table 2.9 Literature about factors affecting networks formation

Author (Year)	Industry	Data/ Technique	Measures of networks	Variable Examined	Effect
(Uzzi, 1996)	Apparel	Ethnography		Third-party referral networks	
				Previous personal ties	
(Gulati, 1999)	new materials, industrial automation, and automotive products	Panel/ random-effects panel probit	Alliance formation	Centrality: the number of cliques to which a firm belongs	+**
				Centrality: how closely connected a firm is to the rest of the firms in the interfirm network, both directly and indirectly	+**
				The number of past alliance	+**
(Gulati and Sytch, 2007)	Automobile	Cross section/ 3SLS	Joint dependence	Technological complexity	+***
				Performance in the procurement	+**
(Rothaermel and Boeker, 2008)	Bio and pharma	Cross section/ logit and negative binomial regression	Alliance formation Alliance intensity	Complementarity: the sum of the centered ratios of the biotech firm's drugs in development and the pharmaceutical firm's SM&A expenses	+**
				Similarities 1: patent cross-citations	+*
				Similarities 2: patent common citations	-*
				Similarities 3: proximity of patenting propensity	+*

Table 2.10 Literature about explorative and exploitative learning effects on networks formation

Author (Year)	Industry	Data/ Technique	Measures of exploitative networks	Variable Examined	Effect
Powell, Koput, and Smith-Doerr (1996)	Biotech	Longitudinal/ panel regression	Non-R&D ties	R&D ties	+**
Rothaermel and Deeds (2004)	Biotech	Pooled cross section/ structural equation	Alliances for commercialization	Alliances for R&D	+**

2.7.2. Open innovations and the external sources of knowledge

Open innovation arguments (Chesbrough, 2003; von Hippel, 1988) emphasize the importance of external ideas and external paths to market innovation. This "new breed of innovation" (Chesbrough and Appleyard, 2007, p. 57) depends on various sources of knowledge, including universities, suppliers, customers, and even competitors. In the open innovation era, a firm puts more weight on knowledge brokerage than knowledge creation (Chesbrough, 2003; Cohen and Levinthal, 1990). Also, due to the risk as well as opportunity involved in open innovation strategy, the roles of intellectual property rights have increased.

Empirical studies in this stream of research are clustered into three groups. The first group examines the factors affecting external sourcing of knowledge. This group includes broad literature about university-industry collaboration. The second group examines how

the depth and breadth of external knowledge during the innovation process affects performance. The third group examines the factors affecting external paths to market. Licensing literature, for example, falls into this group. A summary of the relevant literature is presented in Table A. 3 and Table A. 4 of the Appendix.

Based on the Carnegie Mellon Survey, Cohen et al. (Cohen, Nelson, and Walsh, 2002) found that start-up firms, especially in the pharmaceutical industry, and larger firms are more likely to utilize external knowledge from public organizations in their R&D projects. The higher propensity of start-up firms and biopharmaceutical firms using university knowledge is consistently reported in other studies (Zucker, Darby, and Armstrong, 2002; Zucker, Darby, and Brewer, 1998). This finding shows that the use of external knowledge depends on firm and industry characteristics.

Indeed, external public knowledge seems to have positive impacts on firms' innovative performance. A study based on a Yale survey (Cohen and Levinthal, 1989, 1990) reports that the more important the university knowledge, the higher the R&D intensity of firms. Cohen and Levinthal interpret this as the importance of absorptive capacity of internal R&D. Another study also reports that using external scientific knowledge increases the innovative performance of firms as measured by the fraction of sales attributable to innovative products (Caloghirou, Kastelli, and Tsakanikas, 2004). Besides the particular source of knowledge, the breadth and depth of external knowledge have an inverted-U relationship with a firm's innovative performance (Katila and Ahuja, 2002; Laursen and Salter, 2006).

There are only a few studies on the relationship between the sources of external knowledge and the governance choice of upstream or downstream innovative activities. However, external public knowledge seems to drive external downstream innovative activities, such as collaboration with public organizations (Fontana, Geuna, and Matt, 2006) or licensing (Gambardella, Giuri, and Luzzi, 2007). As for upstream innovation resources, Veugelers and Cassiman (1999) found that in Belgian firms the likelihood of external sourcing increased when information from competitors was important.

PART I. COMMERCIALIZATION OF PATENTED INVENTIONS

CHAPTER 3. Commercialization: Theoretical Motivation

Technological innovation is, by definition, a new technology (or a new combination of existing technologies) *put into (commercial) use* (Afuah, 2003; Roberts, 1988; Schumpeter, 1942). The efforts required for generating new ideas or combining existing technologies in a new way (or "inventions") is often so distinct from the efforts required for transforming those new ideas or technologies into commercial use (Roberts, 1988; Teece, 1986) that, as Schumpeter (1942) asserted, the former "does not necessarily induce innovation, but produces of itself … no economically relevant effect at all." Commercialization is an important issue both in practice and in theory. The competitiveness crisis of the United States in the 1970s and 1980s was not a crisis in generating new scientific and technological ideas but a crisis in transforming them into commercial applications. Inventions of no or little commercial use can be beneficial to the inventor or a society but not as much as the inventions successfully commercialized. Also, in this era of an exploding number of patent filings (Kortum and Lerner, 1999), nonused patents are not only costly for the owner to maintain (Rivette and Kline, 2000) but also detrimental to the competitiveness and technological progress of a society (Shapiro, 2000).

While the importance of commercialization in innovation has been recognized for a long time, it has not been reflected in empirical studies in innovation literature. Most empirical

literature has focused on the inventive part of innovation and, thus, severely overlooked the commercialization part. Moreover, many studies regard inventions as a proxy for innovation, which is, indeed, distinct from invention. A probable contributor to this research trend is a wider and easier availability of data measuring the efforts and outcomes of the inventive part of innovation than similar data measuring commercialization. Patent data is one of the most widely used data sources for this purpose.

Patents are one of the most important sources of innovation studies for numerous reasons. First, patentability requires novelty, non-obviousness, and commercial applicability that conforms to the definition of innovation, especially the inventive part of innovation. Second, by law in most countries, patentability is rigorously scrutinized by professional examiners, and the results are published for public access. Third, patent publications are well-maintained, regularly updated and corrected, and accessible easily at small cost. In summary, patent databases are the largest databases for innovative ideas. Patent data also have several weaknesses. First of all, patented inventions do not cover all inventive activities. Lots of inventions are kept secret (Cohen, Nelson, and Walsh, 2000). However, some recent trends such as the increasing propensity to patent (Hall, 2004; Hall and Ziedonis, 2001; Kortum and Lerner, 1999) and the growth of patentable inventions (Kortum and Lerner, 1999) mitigate this problem. Secondly, they can reveal only a partial picture of innovation because they do not provide information about whether or how the innovative activities are commercialized. To complement this weakness, some direct measures of innovation, such as expert assessment of new products and processes (see,

for example, Acs, 2002; Pavitt, Robson, and Townsend, 1987), are suggested. However, this method requires enormous effort collecting and validating the data.

This study takes advantage of direct and indirect measures of innovative activities by constructing a comprehensive data set from multiple information sources, including patent bibliometrics and a large-scale inventor survey. Based on this novel data set, we aim to answer an important policy and management question about how and what patented inventions are transformed into innovation. In particular, this study examines what determines the commercial uses of patents. Pioneering studies by Teece (1986, 2006) suggest that the profit from innovation is not necessarily appropriated by the innovator but may accrue to the imitator or the owner of complementary assets depending on the maturity of technology, regimes of appropriability, and the characteristics and position of complementary assets. Recent literature about licensing endorses a part of Teece's arguments by empirically showing that the strength of patents (Arora and Ceccagnoli, 2006; Gambardella, Giuri, and Luzzi, 2007; Gans, Hsu, and Stern, 2006; Kim and Vonortas, 2006) and the ownership of complementary assets (Gambardella, Giuri, and Luzzi, 2007) are important predictors for licensing propensity.

We regard a patented invention as *commercialized* when it is used for any of the following purposes: integration into products or processes, licensing and cross-licensing, and establishing a new company to exploit the invention. Patented inventions that are not commercialized are those that are simply not used (i.e., "sleeping patents") or are not used but indeed strategically exploited (i.e., "strategic nonuse patents"). Naturally,

patents of higher technological or economic significance will have higher chances of commercialization. Other factors at the organizational and invention levels should also predict the propensity to commercialize a patented invention. This part examines the effects of evolutionary stages of technology development and firm assets on the commercial uses of patented inventions. We theorize the relationships of particular types of use and the factors at organizational and invention levels in the later part of this study. Most factors affecting the mode of use, in particular different modes of commercialization, we theorize, have offsetting effects on commercialization. Two factors examined in this part, we contend, have a larger unilateral effect on commercialization than the offsetting effects and are, therefore, empirically identifiable. Also, while evolutionary explanation of technological development has been widely accepted, empirical evidence on it in the innovation context is scarce. Although some studies point out firm assets as a driver of non-practicing strategic patents, their impact on commercialization is not well-known. Considering that strategic nonuse accounts for a large share of nonuse patents (38% in our sample), studying the effects of firm assets on commercialization may look like almost a mirror of the study that examines its effects on strategic nonuse. However, there is a subtle difference in interpretation and more explicit difference in policy implications. The above reasons motivate us to examine the effects of two factors on commercialization.

We argue that the patented inventions in mature technology are more likely to find a path to commercial applications because of the incremental nature of innovation and the lower degree of uncertainty. Also, we argue that the patented inventions from capital-intensive

firms are less likely to be commercialized because of the resistance to cannibalizing the existing competitive advantage, progressively increasing organizational rigidity with size, and a larger protective value than the commercialization value of patents.

3.1. Maturity of Technology and Emergence of Dominant Design

Similar to Kuhnian notions of scientific progress (Kuhn, 1970), technological development is known to take a staged trajectory. A new technology, by definition, implies a radical departure from past practice (Abernathy and Clark, 1985). Therefore, in its early stages of development, the economic prospects and utility of a new technology are not fully revealed to the industry players. Before a dominant design appears, investment in the manufacturing process is suppressed because of uncertainty and risk in commercialization, and firms compete for design and industry standards. Once a dominant design emerges, the field of technology is populated with a myriad of incremental innovations that address small technical problems. In this stage, competition shifts from design to manufacturing efficiency. This picture is repeatedly supported by the advocates of technology evolution (Abernathy and Clark, 1985; Dosi, 1982; Henderson and Clark, 1990; Tushman and Anderson, 1986; Utterback, 1994). A common prediction from this lineage of theoretical explanations is that, as a dominant design appears in a technology field, technological uncertainty decreases, the field is populated with many incremental innovations, utility and demands for the technology are widely recognized among firms, and manufacturing processes and facilities are standardized.

We argue that the overall characteristics of technologies in their post-dominant design era constitute a selection environment in which the odds of commercializing a particular technology are higher. Nelson and Winter (1982) proposed four elements that affect the selection environment of technological advancement: 1) the nature of the benefits and costs that are weighed by the organizations that will decide to adopt or not to adopt a new innovation; 2) consumer preferences and institutional environments that affect profitability from innovation; 3) prospects of profit growth; and 4) the difficulty of imitation and learning effects. These elements should vary, more or less, by industry sectors and individual firm characteristics. However, apart from sectoral heterogeneity, increased levels of familiarity with technology and well-established demands and supplies of complementary technologies, which are a defining characteristic of the post-dominant design stage of technology evolution, would constitute a favorable selection environment for a member technology. This argument is particularly related to the first and the last element of Nelson and Winter's selection environment. First, if there is a well-populated group of users or developers for a technology, an innovator in that technology area benefits from monitoring others about which innovations perform well or poorly (Nelson and Winter, 1982). The learning effects occur both at technological (Wade, 1995) and organizational dimensions (Abrahamson, 1991; Hannan and Freeman, 1977). Second, a large population of components in a technology will reduce the costs of implementing a similar technology. If adoption of a technology goes beyond a certain point, complementary factors required for adopting it will be readily available to the innovator. The complementary factors include organizational routines, skills,

complementary technologies, manufacturing processes, and others. Third, the well-populated technology area will have positive impacts on the innovators' aspirations for the benefits. Albeit too simplistic, we argue that at least an established level of demands will favor adopting a technology.[12] In his recent reflection on the original 1986 article, "Profiting from technological innovation," Teece (2006) provides a refined view of the relationship of the emergence of dominant design with the profitability and commercialization of innovation. Teece's remedy for profiting from innovation in technologies where a dominant design has not emerged is to wait until a dominant design emerges, unless the innovator has the capability to promote one. Our argument elaborates on Teece's framework.

Besides the macroevolutionary aspects of technological development, emergence of a dominant design (or mature technology) influences the propensity to commercialize in a more nuanced way. According to transaction cost economics (Williamson, 1981), market transaction of technology will be suppressed when it involves more technological uncertainty (Arrow, 1969; Oxley, 1997). When market transactions are either risky or costly, the innovator will face two options available for his existing patented inventions: 1) to integrate them into his own commercial applications or 2) if the first option is not appropriate, then to seek another option which includes just putting them on the shelf or using them for strategic purposes such as bargaining chips in cross-licensing negotiations or blocking competitors (Grindley and Teece, 1997; Hall and Ziedonis, 2001). The first option is a choice between two different modes of commercialization (or "within-

[12] However, this argument is incomplete unless the following aspects regarding firm-specific and invention-specific factors are not considered together: competitive environment, the amount of the benefits from innovation, and the uncertainty/risk involved in realizing the benefits.

effects"), which, resultantly, would not affect the overall propensity to commercialize. The second option is a choice between commercialization and non-commercialization (or "between-effects"). In a regime where technological uncertainty is high, the propensity to commercialize will decrease because of the between-effects. The between-effects are composed of, among others, plain nonuse (or "sleeping") patents and strategic nonuse patents. All else equal, we postulate that otherwise commercializable (or licensable) patents are strategically exploited rather than put on the shelf. This is consistent with Merges' views (1994) that technological uncertainty induces bargaining failure and results in blocking patents. The arguments developed here are first explored in this part and further examined with particular focus on strategic nonuse in Part III.

Some technology-based products are built on complex integration of technology components, while some other products are built on a relatively simple composition of technologies. Semiconductor or electronics goods typically integrate several hundreds to several thousands of technological components, many of which are complementary and cumulative. On the other hand, pharmaceuticals or agricultural goods are built on a relatively small number of technological components (Cohen, Nelson, and Walsh, 2000). In complex industry, utility and commercialization of a new technological component is determined in the relationship with other technological components and fitness with the final system. Introduction of a new technology cannot be instantly integrated into a commercial product because developing and optimizing with interfacing and complementary technologies will require a certain level of familiarity with that

technology. Therefore, familiarity with a technological component among the system builders will be more influential on commercialization in complex industry.

3.2. Capital Intensity

One superior technology does not ensure commercial success. Successful commercial transformation of an invention generally requires investment in downstream complementary assets such as manufacturing facilities, distribution channels, or marketing capabilities. Indeed, surveys of R&D managers of U.S. firms showed that appropriability of innovation depended crucially on non-technological firm capabilities such as lead-time advantage, complementary assets, or scale economy of manufacturing processes (Cohen, Nelson, and Walsh, 2000; Levin et al., 1987). While firms already equipped with such capabilities are advantageous in product market competition probably due to faster time to market and a learning curve advantage, they tend to be resistant to incorporating new technologies into the existing facilities for the following two reasons: First, innovation requires adaptation of existing complementary assets. A firm will upgrade or replace the existing facilities to accommodate new technologies if it believes that the investment is financially justified (i.e., when benefits from integrating the new technologies surpass the investment). The costs for changing existing plants and facilities to integrate a new technology will be generally larger for a large plant or facility. Hence, in more capital-intensive firms, even the same invention would incur more costs of integration and be subject to stricter cost justification. The higher switching costs in

capital-intensive firms, therefore, will have effects to suppress integrating new incremental technologies. However, the switching costs effects do not necessarily lower the probability of commercialization because the owner of technologies will have another commercialization option: external commercialization (e.g., licensing). Therefore, we need to take a closer look at the mode of commercialization. This will be the topic of Part II.

Second, capital-intensive firms have alternative means of appropriability that can exceed the benefits from commercializing an invention. In other words, capital-intensive firms would worry that new technologies would cannibalize the existing competitive advantage.[13] To illustrate the arguments, let us take an example of liquid crystal display (or LCD) manufacturers. In the LCD industry, production efficiency crucially depends on how big the manufacturers can make a glass substrate (from which LCD panels are cut) and, therefore, LCD manufacturers race for technology development to enlarge the size of the glass substrates. In 2003 Samsung Electronics, then the world's largest provider of TFT-LCD display panels, announced that it would skip the sixth generation and move directly to the seventh generation (Business Wire, 2003). It also announced an additional investment in the existing fifth-generation production line. Definitely, Samsung had a sufficient level of technology to build a sixth-generation production line, but it did not because the huge investment in the sixth generation would not be justified given the competitive advantage in the existing fifth generation and more efficiency gains from the

[13] A study on 192 business units in three highly competitive and turbulent industries shows that the willingness to cannibalize is indeed negatively associated with specialized investments (Chandy and Tellis, 1998). In this study, we assume that high capital intensity would involve a high level of specialized investment.

seventh generation. The arguments made here are in line with Schumpeter's "creative destruction" concept (Schumpeter, 1942) and also with Christensen's reasoning on why the incumbent often fails in radical innovation (Christensen, 2003). The "cannibalization" effects will suppress the external mode of commercialization as well as internal commercialization because either one will weaken the already-existing competitive advantage stemming from the assets. The cannibalization effects of the capital assts on commercialization will be first examined in this part and then in more detail using a direct measure (i.e., whether or not an invention is competence-destroying) in Part II.

In addition, when a firm has expensive and crucial capital assets based on technologies, they would file for patents on some peripheral technologies not directly transformed into commercialization but related to protecting the assets (Ceccagnoli, 2009). In other words, capital-intensive firms will be more attracted to having preemptive patents. The larger incentives to protect at a firm with high capital intensity will also suppress licensing. The risk for dissipation of capital advantage will increase through a competitor's access to the key technology and potential leakage of knowledge used for building the firm's production facility. Turning again to the Samsung case: While Samsung did not build the sixth-generation lines, they kept patenting for technologies used for the sixth generation. Some of these patents would have been filed for in the prospect of jumping into the sixth generation before the decision to skip it, and then filed for strategic reasons such as avoiding potential litigation and blocking or slowing down competitors' technology development. From the interviews with managers in the semiconductor industry, Hall and Ziedonis (2001) found that firms that had sunk large costs into manufacturing facilities

had large incentives to use patents for a safeguard against the threat of costly litigation as well as “bargaining chips” in licensing negotiation. In summary, patented inventions from capital-intensive firms will be less likely to commercialize because the patents may have a larger value in preemption. This argument will be examined in more detail in Part III.

CHAPTER 4. Data and Measures

4.1. Data

In order to address the research questions and hypotheses in this study, we need detailed information about both the outcome of an invention (i.e., its value and use) and the invention activities, including the resources invested, the sources of knowledge, and others. The estimation was based on a novel data set constructed from multiple sources: an inventor survey, the United States Patent and Trademark Office online database, the EPO Worldwide Patent Statistical Database (henceforth, PATSTAT) provided by the European Patent Office, and COMPUSTAT for firm financial information. A key element is the inventor survey (GT/RIETI Survey 2007) that was administered by a research team at Georgia Tech in cooperation with the Research Institute of Economy, Trade and Industry of Japan (RIETI) between June and November 2007.

The GT/RIETI Survey is sampled from the granted U.S. patents filed between 2000 and 2003 (in terms of the first priority application date) and included in the OECD's Triadic Patent Families (TPF) (OECD, 2006). The TPF includes only those patents whose applications are filed with both the Japanese Patent Office (JPO) and the European Patent Office (EPO) and granted in the United States Patent and Trademark Office (USPTO). We used TPF as a sampling basis for several reasons. First, the inventor survey was part

of the project for the U.S.-Japan comparative studies. TPF has an advantage in reducing home-country bias that might stem from a single patent office (Criscuolo, 2006). Second, we could identify inventor addresses easily from multiple patent databases, especially from matching patents filed with EPO. Third, the value of patents is known to be highly skewed. By using TPF we focus on important inventions. One caveat here is that this characteristic of TPF may favor large and multinational firms and also commercializable inventions because the additional costs for filing and maintaining patents in multiple jurisdictions may work as a threshold for low-valued (ex ante) or less-promising patents.

We randomly sampled 28% (or 9,060) of patents stratified by NBER (National Bureau of Economic Research) technology class (Hall, Jaffe, and Trajtenberg, 2001). Then, for the first U.S. inventor of each patent, we collected U.S. street addresses mostly from the EPO database and from other supplementary sources such as the USPTO application database or phone directories. If no address was available, we took the next U.S. inventor. After removing 18 patents that were either withdrawn or for which we could not find any U.S. inventor address we had 9,042 patents for mailing out. Taking the first available U.S. inventor as a representative inventor of each patent, we had 7,933 unique inventors. We took the strategy of not sending multiple surveys to the same inventor, believing this strategy would increase the response rate. In order to select one patent per inventor, we randomly drew one patent out of multiple patents belonging to the same inventor. Then the number of patents belonging to each unique inventor was recorded to use as a weight. Inventor weights range from 1 to 7 as shown in Table 4.1.

Table 4.1 Number of patents per inventor

# Patents per inventor (weight)	Frequency	Percent
1	7124	89.8
2	624	7.9
3	115	1.4
4	43	0.5
5	13	0.2
6	10	0.1
7	4	0.1
Total	7933	100.0

The first round of the survey questionnaires was mailed to 7,933 unique U.S. inventors in June 2008 and the second round to almost 5,000 inventors in July 2008. Between the two rounds, we sent a reminder/thank note to all inventors in the sample. We had received 1,919 surveys via mail and web with a response rate of 24.2% (when adjusted for the undeliverable addresses and the deceased, the response rate increased to 31.9%). Then we tested response bias, mail vs. web bias, and good vs. bad address bias using the patent indicators for all patents in the sample. The test results did not show significant differences between any two groups compared. In particular, there were no significant differences in average values of patent indicators between two compared groups. This also indicates that the sample is not significantly biased due to inventor attrition (indeed, we received 20 or so responses from a family member of the deceased or seriously ill

inventors). Because our survey was directed toward the inventors rather than managers of firms, the sample should not be seriously affected by firm attrition.[14]

In our survey, 1,806 responses are from inventors affiliated with firms (either public or private).[15] We identified firm patents from the survey but also from assignees of patents for those responses missing on the survey question. In the survey, inventions from large firms (employees > 500) account for 81.1% of all inventions affiliated with firms, mid-sized firms for 7.7%, and very small firms (employees < 100) for 11.2%.[16] The figures go a little bit upward for large firms and downward for small and medium firms when they are weighted (see the rightmost bar of Figure 4.1). In order to draw a comparative picture of the distribution by firm size of the survey, we compared it with the distribution of the total sales amount of firms in 2002 by their sizes[17] (i.e., "very small" if the number of employees is less than 100; "large" if the number of employees is greater than or equal to 500; "medium" for firms with the number of employees in between). The baseline benchmark is the 2002 U.S. economic census data (U.S. Census Bureau, 2006). Compared with the leftmost bar of Figure 4.1, which is directly calculated from the census data, our survey seems to overrepresent large firms (61.9% v. 82.5% weighted for large firms) and underrepresent small and medium firms (26.5% v. 10.5% weighted for

---

[14] However, attrition of firms may have affected some questions in the survey. For example, "no commercialization" or "don't know" answers in patent use questions may have been inflated from inventions assigned to a firm that went out of business because of the following reasons: First, they might have been disadvantageously positioned in commercialization; second, their use might not be properly tracked by inventors. Nevertheless, this may not be a serious source of bias because the legal status of an inventor of a patent is not tempered by a change of assignee firm.

[15] This figure does not count independent inventors.

[16] Note that the number of employees asked in the survey is not for a single establishment but for a group of related firms. When the firm is a subsidiary of a larger organization, the survey question asks the respondent to report the number of total employees of its parent firm and other subsidiaries.

[17] The distribution of the total number of employees by firm size is also similar with the sales distribution.

very small firms). However, note that the survey counts the number of patents while the census calculates sales amount. Because innovativeness and patent propensity are known to differ by firm size, we calculated two adjusted distributions. The second bar of Figure 4.1 reflects the different innovativeness between large and small firms. Using the innovation data from the Small Business Administration, Acs and Audretsch (1988) found that, in highly innovative sectors, large firms generated, on average, 1.272 times more innovative products than small firms. The second distribution is calculated by multiplying large firm sales by 1.272. The gap between the distribution of this and our survey now becomes closer than the non-weighted one. However, this figure is still not about patent distribution and may not be directly comparable with the patent distribution of our survey. The third bar shows the distribution of sales amount by firm size adjusted for the patent propensity.[18] Our survey results show a slightly lower proportion for large firms and slightly higher proportion for very small firms but more or less show similar distribution with the "innovative sales" calculated from the census and the patent propensity provided in the literature. In summary, our sample distribution is consistent with the overall distribution of innovative firms as the patent data would be but not with the distribution of all firms.

[18] To calculate the patent propensity, we first calculated deflated R&D expenditure by firm size. We applied a uniform R&D intensity of 2.9% as provided by the Carnegie Mellon survey. We also tested other values of R&D intensity to find no notable changes in the overall pattern. Then we calculated "innovative sales" by applying the probability function of firms' having non-zero patent conditional on the R&D expenditure (or simply call it patent propensity function). We used Scherer's (1983) Weibull distribution with the estimated deflated R&D expenditure tapped in. Based on the descriptive statistics provided by Scherer we corrected small R&D part as follows: Pr(# patent>0) = $1 - e^{-0.0104 * R\&D^{0.647}}$ for large firms and $1 - e^{-0.0104 * R\&D^{0.647}} + 0.126$ for small and medium firms. Caveat: The estimation here is only a rough benchmark because it is based on the old data and because industry heterogeneity is not fully considered.

The proportion of start-up firms is much higher for very small firms (26.2%) than for large firms (2.6%) and statistically significant at 0.01 level (Pearson Chi-square =187.7; Pr = 0.000).

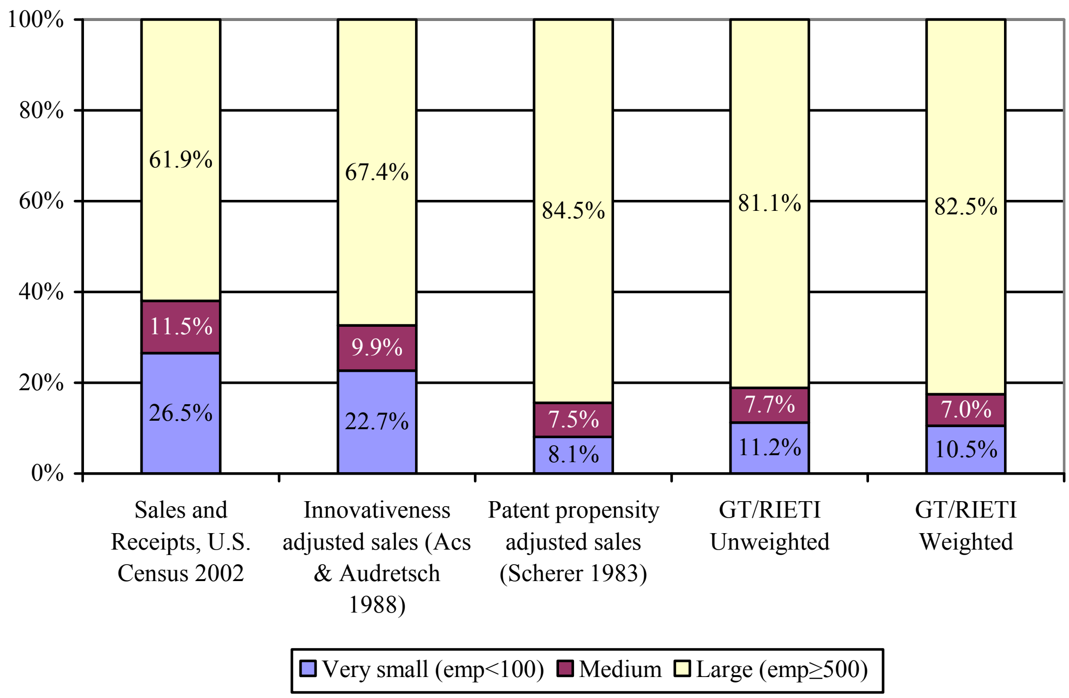

Figure 4.1 Distribution of sales and patents by firm size
Data sources: (Calculations from U.S. Census Bureau, 2006)

Among these, 107 responses did not provide any information about how they used patents, which is our dependent variable. Further, 460 observations have missing or

unreliable values on one of our independent or control variables.[19] After a listwise deletion of observations having a missing value on any variable, we have 1,239 complete cases. Because this drop is huge, we examined whether this listwise deletion of missing values causes bias. For the most of our patent-level variables (e.g., commercialization, technology class, firm size, number of inventors, and others) there is no statistically significant difference in means between the complete cases sample and the full sample. Significant biases are caused by the variable of technological value of patents. Therefore, we test our models both with and without this variable. Furthermore, we test the self-selection effects of the respondents' opting-out from answering this question on our model specification using the Heckman selection model. Further details will be discussed in analysis.

4.2. Variables and Measures

4.2.1. Dependent Variables

The GT/RIETI survey asks respondents whether the patented invention was commercially used and, if not, why it was not. The modes of commercial use asked include 1) commercialized in a product/process/service by the applicant/owner, 2) "licensed by (one of) the patent-holder(s) to an independent party," 3) if the patent is licensed whether it is a part of a cross-license, and 4) whether the patent was commercially exploited by the respondent or any of respondent's co-inventors for starting a new company. First, we constructed a variable "any use" by coding it 1 for the patented

[19] For example, the sum of all types of R&D efforts should be 100%. We removed those observation whose sum of R&D efforts are not either 99% or 100%.

invention falling in any of these three categories. We coded 0 for those observations who explicitly reported that the patented invention was not used for all three commercial modes. Some answered to only some of these three questions. This affects identifying nonuse. In the survey, then, we asked for the reasons a patent was not used. Thus, we regard those observations who answered to the reasons for nonuse but only partially reported nonuse in the three use questions as nonuse. Out of 1,239 complete cases, 657 (53.0%) patents are reported to be used. There will be some gap between the time when an invention was completed and the time when it was put into actual use. Also that gap may vary by industry- or technology-specific factors. All patents in the sample were first filed[20] between 2000 and 2003 inclusive, but the granted date spans from 2000 to 2006. Therefore, we tested whether the rate of actual use of patents differs by the year filed or issued. Unequal variance t-test shows that there are no significant differences between the two groups in terms of issue year and filed year.[21]

4.2.2. Explanatory Variables

We operationalize technological maturity using the familiarity index of technological components devised by Fleming (2001). The component familiarity captures the degree to which a patentee is familiar with the technological components that were used in his patent. The basic assumption is that as a technology matures (therefore, the population of technological artifacts increases), technological trajectories based on this technology

[20] Indeed, the first priority patent in the triadic family.

[21] The chi-square test results show significant differences in issue year by used2 (chi-sq statistic=11.84 with d.f.=5, prob=.0371). However, the trends are not clearly monotonic, although year 2001 had the highest ratio (67.44%) and 2006 the lowest (48.21%). The second highest ratio of commercialization was shown in year 2005 (56.41%). Therefore, we could not confirm that commercialization should be right truncated in the sample.

become more foreseeable (Dosi, 1982). Component familiarity, as suggested by Fleming, averages the number of patents previously assigned to the same technology classes as the focal patent and applies a knowledge attenuation factor by temporal distance between the focal patent and the referred patents. He has empirically shown that component familiarity had an inverted-U relationship with the uncertainty of utility of the patent as measured by the variation of forward citation counts.

In order to construct this variable, first we count the number of U.S. patents filed from 1976 to 1999 in each technology class.

Component familiarity for patent i =

$$\frac{1}{N_{C_i}} \sum_{c_j \in C_i} \sum_{\substack{\textit{all patents k filed} \\ \textit{from } 1976 \textit{ to } 1999}} 1\{\textit{patent k assigned to subclass } c_j\} \times \textit{kattenuation}_k$$

Where $C_i = \{\text{patent subclass assigned to patent i}\}$,

c_j = patent subclass identifier,

N_{C_i} = number of different patent subclasses assigned to patent i.

And knowledge attenuation factor, $\textit{kattenuation}_k$ =

$$\exp\left(\frac{\text{temporal distance of patent k}}{\text{time constant of knowledge loss}}\right),$$

Where temporal distance of patent k=

4.5 if patent k was filed from 1995 to 1999

9.5 if patent k was filed from 1990 to 1994

16.5 if patent k was filed from 1976 to 1989

Time constant of knowledge loss is set to 5 following Fleming (2001). We rescaled component familiarity by dividing it by 1,000.

Complex technology areas are identified using the survey. The GT/RIETI survey asks the inventors “how many domestic patents are jointly used in the commercial application of the invention.” It provided eight categories: 1, 2 to 5, 6 to 10, 11 to 50, 51 to 100, 101 to 500, 501 to 1,000, and more than 1,000 patents. We averaged the median values over 30 subgroups of technologies and constructed a variable, “technological complexity.” Then, a dichotomous variable, complexity of product technology, is coded 1 if the technological complexity of the subclass to which the focal patent belonged was higher than the median value of technology complexity. The complex technologies classified in this way include information technology, semiconductors, telecommunication, electronics, biotechnology, and chemical engineering. The non-complex (or discrete) technologies include textile, pharmaceuticals, agriculture and food, construction, and transportation. This classification is consistent with the previous literature (Cohen, Nelson, and Walsh, 2000; Kusunoki, Nonaka, and Nagata, 1998; Reitzig, 2004) but, we believe, more evidence-based.

Following Hall & Ziedonis (2001) and Ziedonis (2004), we measure capital intensity using the deflated book value (constant U.S. dollars in 2000) of property, plant, and equipment divided by number of employees. In order to mitigate yearly fluctuation and reduce missing values, we use a three-year running average centered on the filed year of a focal patent. Main data sources are COMPUSTAT North America–Fundamentals Annual and COMPUSTAT Global–Fundamentals Annual.[22] For a few firms, we directly found

[22] We use consolidated financial reports. Therefore, many subsidiaries in our sample are regarded as a parent company whose financial information is available.

the data from their web sites. In the sample, about a quarter of the firms are either private or foreign whose financial information is not available in either the COMPUSTAT or alternative sources mentioned above. They are coded as a dummy variable named "dummy for missing capital intensity."

4.2.3. Controls

We control the area of technology, the technological value of the focal patent, the nature of invention (product vs. process), initial purpose of the research that led to the patented invention, the proportion of R&D efforts devoted to the basic research, technological breadth of patents as measured by the number of different technological classes belonging to the focal patent, number of inventors registered in the patent document, the number of independent claims contained in the patent documents, and the logarithm of age of the invention at the time of survey as measured by the incipient date of completed survey subtracted by the filed date of the patent in the months.

Technological assets

We use patent stock as a proxy for technological assets of a firm. Patent stock is calculated as the number of granted U.S. patents assigned to the first assignee in the focal patent and filed before the filed year of the focal patent. Patent stock of firm i for a focal patent filed in year t is:

$$PS_{it}=PS_{i\,(t-1)}(1-\delta)$$

where δ represents the constant depreciation of knowledge, which is set to 15% following the previous studies (Grimpe and Hussinger, 2008; Hall, 1990).

Similar to the way we construct the capital intensity, subsidiary firms are consolidated into their ultimate parents. Patent stock of merged and acquired firms is also consolidated into the merger. We use the PATSTAT database (April 2008 version) compiled by the EPO. There are two advantages using the PATSTAT for this purpose. First, the PATSTAT provides relational tables and an SQL interface for the bibliometric information of the U.S. patents, which make data extraction much easier than other available data sources. Second, PATSTAT provides standard ID numbers of assignees, which corrected many small differences in spellings. We further cleaned the data by manually searching and correcting the list of assignees in our sample.

External knowledge flows

The GT/RIETI survey asks how important the various knowledge sources were in either suggesting or completing the research that led to the patented invention. The measure is a six-point Likert scale with 0 for "did not use," 1 for "not important," and 5 for "very important." The sources listed are scientific and technical literature, patent literature, fair or exhibition, technical conferences and workshops, standard documents, universities, government research organizations, customers or product users, suppliers, competitors, and others. Responses in the others category include consultant, education, or experience. Then we identified six items (patent literature, fair or exhibition, standard documents,

customers or product users, suppliers, and competitors) as “industrial knowledge” and the remaining four items (scientific literature, technical conferences and workshops, universities, and government research organization) as “public knowledge.”

External collaboration

It is well known that networks affect the outcomes of innovation (Afuah, 2000; Dyer and Nobeoka, 2000; Gulati and Higgins, 2003; Gulati and Sytch, 2007; Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Deeds, 2004; Shan, Walker, and Kogut, 1994). The network literature consistently finds that firm performance is positively associated with R&D collaboration (Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Deeds, 2004), networking with suppliers (Dyer and Nobeoka, 2000; Gulati and Sytch, 2007), or quality of networks (Powell, Koput, and Smith-Doerr, 1996; Uzzi, 1996). The GT/RIETI Survey asks whether the focal patent was developed with inventors who belong to various external organizations and whether the focal patent was developed through formal or informal collaboration with external organizations. The survey presents 8 distinct categories for external organizations including suppliers, customers and product users, competitors, non-competitors within the same industry, other firms, universities, government research organizations, hospitals, and other. We construct a collaboration dummy variable by coding 1 for the inventions with any external collaborators.

Inventor in manufacturing unit

In Teecian arguments, the complementary assets interfere with mode choice of innovation in three different points. If the invention does not require complementary

assets, it is immediately commercialized by the inventor. When the invention requires complementary assets for commercialization, the degree of specialization and the ownership of those assets play a role. Empirically, it is hard to assess whether a particular invention requires complementary assets for its commercialization and how specialized those assets should be. Therefore, we assume that every invention requires a certain type of downstream assets, such as manufacturing facility, and that those assets are somewhat co-specialized. An invention from a manufacturing unit is already, or ready to be, coupled with downstream co-specialized assets. The GT/RIETI survey asks which organizational unit the inventor belongs to. A variable "Inventor in manufacturing unit" is coded 1 if the inventor belongs to the manufacturing unit and 0 for the R&D unit (either independent or sub-unit attached to non-R&D function), software development, sales and marketing, and others.

R&D for base technology

This variable discriminates the business needs of the invention. Using our survey, we code 1 for this variable if the reported purpose of research is "enhancing the technology base of the firm or the long-term cultivation of technology seeds."

Proportion of basic R&D

This variable is a proxy measuring the position of the invention on a basic-applied spectrum. In the survey, we asked the inventor how much effort (in percentage) he put into basic research. The other categories presented are "applied research," "design and/or development," and "technical services."

Technological value of patents

In our survey, we ask the inventor to assess the technical significance of the invention relative to other technical developments in the field during the year the focal patent was applied for. We code 4 for the top 10%, 3 for the top 25% (but not top 10%), 2 for the top 50% (but not top 25%), and 1 for the bottom half.

Number of inventors

We control the number of inventors as registered in the U.S. patent publication.

Type of innovation

Product innovation is observed to differ in some aspects from process innovation (Cohen, Nelson, and Walsh, 2000). Therefore, we controlled for the type of innovation. A variable "product innovation" is constructed from the survey. The reference category is composed of process innovation or mixed innovation in which product and process innovation are mixed.

Number of claims

We control the scope of patent by including the number of independent claims. Each claim may be regarded as an independent patent (Tong and Frame, 1994)[23] and, thus, the number of claims is known to measure the breadth of utility or applicability of the patent. In U.S. patent law, there are two types of claims: independent and dependent or multiple

[23] In judging patent infringement in the U.S., infringing any single claim in a patent is regarded as infringement on the patent.

dependent. While an independent claim stands alone, a dependent claim refers to a claim previously set forth and specifies a particular embodiment or limitation of the invention (35 U.S.C. 112). Because of this distinction, counting dependent claims may not (or in a fractional way) properly reflect the technological scope of inventions. Therefore, we count only the independent claims. We regard any claim that contains a reference to another claim as a dependent claim and subtract them from the total number of claims. We take a natural logarithm of it, assuming marginally decreasing nonlinear effects.

Age of invention

The mode of use may vary by the length for which an invention has come out and been publicized. The variable "age of invention" measures how many months have elapsed at the time of the survey since the invention was filed.

Industry dummies

We distinguish six different industries using OST/INPI/ISI nomenclature[24] based on International Patent Class.

[24] This is a widely used nomenclature, especially among European researchers, focusing on industry characteristics. This system was developed and updated by three European research institutes: the Observatoire Science et Technology, the INPI (Institute Nationale Proprieté Industrielle), and Fraunhofer Institute for Systems of Innovation Research.

Table 4.2 Variables and descriptions (N=1239)

Variable	Mean	Std. Dev.	Min	Max	Data source
Any commercialization	0.530	0.499	0	1	Survey
Explanatory variables					
Component familiarity (/1000)	0.087	0.159	0	2.489	USPTO
Capital intensity (M$/employee)	0.073	0.118	0	1.086	COMPUSTAT
Dummy for missing capital intensity	0.262	0.440	0	1	COMPUSTAT
Controls					
Large firm (employees > 500)	0.859	0.348	0	1	Survey & Patent
Ln(patent stock)	5.466	2.753	0	9.865	PATSTAT
Inventor in manufacturing unit	0.084	0.277	0	1	Survey
Industrial knowledge	0.268	0.189	0	1	Survey
Public knowledge	0.266	0.208	0	1	Survey
Dummy for collaboration	0.293	0.455	0	1	Survey & Patent
Technological value	2.211	1.069	1	4	Survey
No immediate demand	0.224	0.417	0	1	Survey
% Basic R&D (/100)	0.082	0.176	0	1	Survey
Product invention	0.513	0.500	0	1	Survey
Man-month (normalized)	0.182	0.229	0	1	Survey
Number of inventors	2.796	1.911	1	16	Patent
Complexity of technology (# USPC)	4.431	3.535	1	30	Patent
Number of claims	22.826	15.689	1	181	Patent
Age of invention (months)	68.873	12.029	37	92	Patent
Electrical engineering	0.256	0.437	0	1	Patent
Instruments	0.209	0.407	0	1	Patent
Chemistry, pharmaceuticals	0.237	0.426	0	1	Patent
Process eng., special equipment	0.136	0.343	0	1	Patent
Mechanical eng., machinery	0.134	0.341	0	1	Patent
Consumer goods & Construction	0.027	0.163	0	1	Patent

CHAPTER 5. Analysis and Results

5.1. Sample Characteristics

In the sample, 53.0% of patents are commercialized in any of the following three modes: internal, licensing out or cross-licensing, or using for establishing a new firm. Surprisingly, despite the recent surge of patent filing in the United States, the rate of commercialization is quite similar to that of about a half century ago. One study conducted during the late 1950s reports that the rate of use of the U.S. patents issued in 1938, 1948, and 1952 was 49.3% at the time of the survey[25] (Sanders, Rossman, and Harris, 1958). However, this rate is much lower than that of European patents. The PatVal-EU reports that about 63.9% of European patents filed between 1993 and 1997 inclusive are used by the time of survey, 2002 to 2003 (Giuri et al., 2007). When restricted to the corporate patents only, this rate will go up further because the reported rate of use for the non-corporate patents is a little bit lower than corporate patents. However, it is worth reminding readers here that these two references are not directly comparable to our survey for two reasons. First, the GT/RIETI survey asks about more recent patents than the Sanders, Rossman, and Harris survey and the PatVal-EU survey did. Assuming that there should be a time premium of actual use of patents, the rate of use reported in our survey may be underestimated compared to both surveys mentioned.

---

[25] The rate including expected use during the full lifetime of patents calculated by Sanders, Rossman, and Harris is about 57.2%.

The second reason, on the other hand, contributes to overestimating actual use. Considering that sampled patents of our survey are triadic patents, we can speculate that the overall rate of use for the patents filed with the USPTO may be lower. The further comparative discussion of the rate of use goes beyond the scope of this study. The dominant mode of commercialization is internal, which accounts for 39.1% of total patents. Licensing and “using for establishing a new firm” account for 9.9% and 5.3%, respectively.

In our sample, 1,064 patents (or 85.9%) are affiliated with large firms. In order to figure out whether our sample overrepresents large firms, we compare it with the PatVal-EU inventor survey (Giuri et al., 2007). The PatVal-EU survey defines a large firm as having more than 250 employees and a small firm less than 100 employees. For comparability, we use the same categories. Certainly, the proportion of large firms in the U.S. patents may not be necessarily similar to that in European patents. However, given that we do not have the statistics of the United States, we use European data for one reference. We may have a slight upward bias for large firms. However, remember that our sampling frame is the triadic patent families, which means that patents should have been filed with at least three offices: USPTO, EPO, and JPO. Additional filing and maintenance costs involved in triadic patent families may have imposed a threshold to hinder a marginal firm from filing in all the three national/regional offices and, consequently, resulting in a higher proportion of large firms than the set of patents filed in a single jurisdiction.

Table 5.1 Proportion of inventions from large firms: comparison with PatVal-EU

	PatVal-EU	GT/RIETI (unweighted)	GT/RIETI (weighted)*
Large firm (> 250 employees)	75.8%	84.7%	85.4%

* We weight by the number of patents assigned to the same inventor in our sample. Note that we did not send multiple surveys to those inventors having more than one patent in the sample. Also note that the number used in this table is different from the estimation sample. In the estimation, we supplemented the firm size information from the GT/RIETI survey with the secondary sources of data.

The rate of commercialization also varies by technology areas. Table 5.2 shows the cross-tabulation of the actual commercialization by the OST/INPI/ISI technology classes. The general trends are the higher commercialization rate for discrete type of technologies, such as mechanical engineering or consumer goods, and the lower rate of commercialization for the complex type of technologies, such as electronics and chemicals. The difference of the rate of commercialization is statistically significant by 30 leaf level of technology areas (P=0.006) and by 6 aggregate level also (p=0.053). The correlation matrix of the variables is reported in Appendix A, with the asterisk denoting the conventional level of significance at alpha < 0.05.

Table 5.2 Commercialization by technology area

OST/INPI/ISI technology area	Not exploited	commercial use	Total	% commercial use
MedicalTechn	49	47	96	49.0%
Telecom	48	43	91	47.3%
Electr/Energy	32	51	83	61.4%
Optical	49	30	79	38.0%
Analysis/Measurement/ ControlTechn	30	47	77	61.0%
IT	31	41	72	56.9%
Handl/Printing	30	38	68	55.9%
Polymers	32	34	66	51.5%
OrganicChem	39	25	64	39.1%
Motors	26	27	53	50.9%
Matprocessing/Textiles/Paper	20	27	47	57.4%
Semiconductors	23	19	42	45.2%
ChemEngineering	23	19	42	45.2%
SurfaceTechn	22	18	40	45.0%
Materials	13	26	39	66.7%
MechElements	14	25	39	64.1%
Audiovisual	22	16	38	42.1%
Transportation	19	17	36	47.2%
Pharmaceuticals/Cosmetics	18	16	34	47.1%
MachineTools	13	20	33	60.6%
PetrolChem/materialsChem	19	11	30	36.7%
ConsGoods	7	16	23	69.6%
Biotechnology	5	7	12	58.3%
Environment	5	7	12	58.3%
Agric&Foods	2	8	10	80.0%
ConstrTechn ;	1	9	10	90.0%
Others*	7	13	20	65.0%
Total	599	657	1256	52.3%

* Aggregated “Agric&FoodProcess-Machines,” “NuclearTechn,” “ThermProcesses,” and “SpaceTech/Weapons”

5.2. Probit Regression Results

Column 1 of Table 5.3 presents the main results of probit regressions in the full sample.

Columns 2 and 3 show the results of probit regressions in the complex technologies

sample and in the discrete technologies sample, respectively. All models are statistically significant and robust against several outliers.[26] To test multicollinearity, we calculated the variance inflation factor (VIF) from OLS regression of the full model. We found no serious multicollinearity as indicated by small VIFs (Cohen et al., 2003). For robustness checks, we also estimated the model with the complete cases for the variable capital intensity (column 4, N=914) and the Heckman selection model with a non-missing dummy as a dependent variable of selection equation (column 5 and 6, N=1795). We found no notable discrepancy between the main results and either the restricted sample model or Heckman selection model.[27]

---

[26] We identified outliers using Cook's D and Leverage. There is no significant difference in the result when we ran the regressions after removing some identified outliers.

[27] Heckman probit selection model (Dubin and Rivers, 1989; Heckman, 1979) corrects self-selection bias by using the Inverse Mills Ratio estimated by the selection equation in the outcome equation. The selection equation is composed of a non-missing dummy (coded 1 if an observation has full information on all the variables and 0 otherwise) as a dependent variable and three independent variables: 1) normalized rank order of the number of citations received, 2) a dummy indicating collaboration, and 3) a dummy indicating whether the invention is related to an immediate demand. We included forward citations count as a proxy of technology value because we suspect that large missing values on the variable of technological value may be systematic. For example, the inventor having low-valued patents may have hidden an honest assessment behind "don't know." The latter two variables are included because means of them between the full sample and the non-missing subset are significantly different. The outcome equation is a binary probit model with "any commercial use" regressed on the covariates and the Inverse Mills ratio calculated from the selection equation. We used Heckman probit function of STATA 10. In the selection equations of Heckman probit estimations, the coefficients on collaboration (positive) and dummy for no immediate demands (negative) are significant. This tells us that, in our survey, the respondents are more likely to give us fuller information when their patents had been developed in a more collaborative way and their initial purpose of R&D project for the patented inventions had been more commercially oriented. However, potential bias that may stem from the self-selection of item non-responses should not affect the overall relationships of our interests. The correlations between error terms (Heckman's rho) are statistically insignificant. This indicates that self selection effects would not result in biased estimates. We also ran probit regressions for the fully constrained sample and the sample having a dummy-adjusted technology value variable, respectively. The regression coefficients of both models are strikingly similar with each other and with the Heckman selection model. There is no change in sign and significance of the coefficients on our independent variables. As for control variables, no change in sign is observed.

Table 5.3 Results of regressions (DV=any commercial use)

Variables	Main results (probit)			Robustness checks	Heckman probit	
	(1) Full	(2) complex technology	(3) discrete technology	(4) Removed missing capint	(5) Main eq. (any commercial use)	(6) Selection eq. (not missing)
Component familiarity (/1000)	0.395*	0.595**	-0.786	0.435*	0.395*	
	(0.227)	(0.270)	(0.753)	(0.257)	(0.227)	
Capital intensity (M$/employee)	-1.027***	-1.721**	-0.472	-0.871**	-1.027***	
	(0.382)	(0.706)	(0.447)	(0.387)	(0.383)	
Dummy for missing capital intensity	0.051	-0.130	0.194		0.051	
	(0.125)	(0.180)	(0.183)		(0.125)	
Large firm (employees > 500)	0.093	0.085	-0.015	0.317	0.093	
	(0.142)	(0.194)	(0.221)	(0.282)	(0.142)	
Ln(patent stock)	-0.054***	-0.048*	-0.063*	-0.081***	-0.054***	
	(0.020)	(0.026)	(0.034)	(0.023)	(0.020)	
Inventor in manufacturing unit	0.337**	0.436**	0.232	0.135	0.337**	
	(0.145)	(0.205)	(0.209)	(0.183)	(0.145)	
Industrial knowledge	0.997***	0.838***	1.148***	1.206***	0.997***	
	(0.233)	(0.307)	(0.365)	(0.274)	(0.239)	
Public knowledge	-1.077***	-1.117***	-0.946***	-1.114***	-1.077***	
	(0.219)	(0.284)	(0.362)	(0.261)	(0.225)	
Dummy for collaboration	0.194**	0.225*	0.137	0.094	0.198	0.281***
	(0.087)	(0.117)	(0.135)	(0.106)	(0.378)	(0.072)
Technological value	0.288***	0.291***	0.302***	0.319***	0.288***	
	(0.038)	(0.050)	(0.059)	(0.046)	(0.038)	
No immediate demand	-0.248***	-0.227*	-0.306**	-0.288***	-0.251	-0.192***
	(0.091)	(0.119)	(0.149)	(0.107)	(0.278)	(0.071)
% Basic R&D (/100)	-0.581**	-0.667**	-0.414	-0.669**	-0.581**	
	(0.235)	(0.300)	(0.402)	(0.277)	(0.237)	
Product invention	0.093	0.150	0.039	0.080	0.093	
	(0.077)	(0.101)	(0.127)	(0.091)	(0.077)	
Man-month (normalized)	0.118	0.116	0.228	0.342	0.118	
	(0.180)	(0.237)	(0.290)	(0.208)	(0.180)	
Number of inventors	0.045**	0.054*	0.044	0.043*	0.045**	
	(0.021)	(0.028)	(0.034)	(0.025)	(0.021)	
Complexity of technology (# USPC)	-0.013	-0.024	-0.011	-0.020	-0.013	
	(0.011)	(0.017)	(0.016)	(0.013)	(0.011)	
Number of claims	-0.002	-0.004	-0.001	-0.004	-0.002	
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	
Age of invention (months)	0.005	0.005	0.006	0.007**	0.005	
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	

Table 5.3 (continued)

Electrical engineering	0.194*	0.131		0.256**	0.194*	
	(0.111)	(0.126)		(0.127)	(0.111)	
Chemistry, pharmaceuticals	0.055	-0.131	0.200	-0.042	0.055	
	(0.121)	(0.213)	(0.174)	(0.144)	(0.122)	
Process eng, special equipment	0.087	0.034	0.278	0.208	0.087	
	(0.135)	(0.167)	(0.229)	(0.156)	(0.136)	
Mechanical eng, machinery	0.103	0.120	0.263	0.204	0.103	
	(0.133)	(0.246)	(0.186)	(0.153)	(0.133)	
Consumer goods & Construction	0.259	0.072	0.919	0.374	0.259	
	(0.270)	(0.320)	(0.592)	(0.378)	(0.269)	
Normalized rank order of forward citations count						0.057*
						(0.032)
Constant	-0.764**	-0.612	-0.973**	-1.053**	-0.778	0.358***
	(0.316)	(0.428)	(0.491)	(0.411)	(1.468)	(0.076)
Heckman's Rho (Arctanh-transformed)					0.026	
					(2.712)	
Observations (censored)	1239	722	517	914	1795 (556)	
Log Likelihood	-761.19	-445.17	-307.34	-558.10	-1859.26	
Wald chi2	180.27	98.56	91.28	140.42	162.12	
Pseudo R2	0.111	0.110	0.136	0.119	.	

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

As expected, the patents of higher technological value are more likely to be commercially exploited. The coefficients on technological value in all models are statistically significant at 1% level and positive. As the R&D project leading to the invention had focused more on basic research or the initial purpose of R&D project was long-term cultivation of base technology rather than current business purpose ("No immediate demand"), the resultant patents are less likely to be commercialized even after controlling for the age of invention. This result implies that commercializing the outcome from basic

R&D is not just a matter of time but there should be a fundamental discrepancy in commercialization between basic R&D and applied R&D.

As the number of inventors increase, the probability of commercialization increases, but resources invested in the invention project as measured by man-month is not significantly associated with the propensity to commercialize. The number of inventors may represent both the amount of resources invested in the invention and, to some extent, the degree of complexity of the invention project. The probability of commercialization is not significantly associated with other patent strength measures (number of claims and number of different technology classes).

Patents from firms with large patent stock are less likely to commercialize. As patent stock increases by 1 percent around its mean, the probability of commercialization decreases by 2.1 percentage points, holding others at their means or modes. After controlling for the size of patent stock, firm size does not affect the propensity to commercialize.

A patent developed by an inventor belonging to the manufacturing unit is more likely to be commercialized. The coefficient of the variable "inventor in manufacturing unit" is statistically significant and positive. Holding other variables at their means or modes, the probability of commercialization for a patent from manufacturing units is lower by 0.141 than a counterpart patent from specialized R&D units or other non-manufacturing units, such as sales and marketing departments.

The probability of commercialization is likely to be higher for collaborative inventions than non-collaborative inventions, holding others constant. The coefficients for knowledge sources are also highly significant. However, the impact of external knowledge on the propensity to commercialize diverges depending on the characteristics of sources. While the industrial sources of knowledge that originated from customers, suppliers, competitors, fair or exhibition, standard documents, or patent literature are likely to increase the propensity to commercialize, the public sources of knowledge, such as published scientific literature, conferences, universities, or government research organizations, are likely to reduce the propensity of commercialization. These effects are statistically significant at 0.01 level and hold even after controlling for collaborations.

Turning to the variables of our interests, adding component familiarity marginally improves the fit and explanatory power of the model compared to the base model with only controls (not reported). The coefficient is also marginally significant at 10% level but the sign is positive as expected. This estimation suggests that patents in familiar technology areas (one standard deviation around its mean) will be commercialized more by 2.5 percentage points, even after controlling for value of technology, demands, and others.[28] The impact of component familiarity is stronger in complex technologies (columns 2 and 3). In fact, to our surprise, the regression coefficient on component familiarity in discrete technologies (column 3) not only loses significance but also

[28] We tested whether there is a curvilinear relationship between the propensity to commercialize and component familiarity by adding a square term in the regression. We found no evidence of that.

changes its sign to negative. This finding indicates that technology evolution may have a different impact on innovation depending on the nature of underlying technology.

In discrete technology, utility and commercial potential of a new technology may be relatively easily foreseeable and work independently from the overall development stage of the field. When nylon was invented, its usage was instantly recognized. Then, to protect profits from nylon, Du Pont scrutinized the possibility of substitutable petrochemical synthesis methods that can be used to make an equivalent of nylon and patented those substitutable technologies. On the other hand, competitors who may have developed substitutable technologies would not want to commercialize them unless their technologies were proved safe from infringement and would result in better performance to compensate the late start. The field was populated with fence patents to prevent rivals' inventing-around the core technology.

The coefficients on capital intensity are significant and negative as expected. The estimation (full model in column 1) suggests that patented inventions from capital-intensive firms ($500,000 per employee above average firm) will commercialize the invention less by 19 percentage points, holding others constant at their means or modes. Also, the impact is stronger for complex technologies. The regression coefficient is -1.721 and significant at 0.05 level for complex technologies but -0.472 and not significant in discrete technologies. Disappearance of significance in discrete technologies may be caused by the small sample size. We cannot explain the reasons

underlying this discrepancy because we do not know exactly how capital assets are differently utilized between complex and discrete technologies.

5.3. Concluding Remarks

We examined the effects of evolutionary stages of technology development and firm capabilities on the commercial uses of patented inventions. We found supporting evidence on the arguments that the patented inventions in mature technology are more likely to find a path to commercial applications because of a favorable selection environment of technology and lower uncertainty linked to the general characteristics of mature technology. Our analysis is consistent with the evolutionary explanation of technology development as claimed by many scholars of innovation studies (Abernathy and Clark, 1985; Dosi, 1982; Henderson and Clark, 1990; Nelson and Winter, 1982; Utterback, 1994). However, the effects of the selection environment are not clearly delineated from the effects of uncertainty on a choice between the external use and nonuse as predicted by transaction cost economics. This is because we deal with commercialization as a homogeneous category. Resultantly, we cannot see clearly the different mechanisms working on different modes of use (and nonuse) in this analysis. In the following parts, this study breaks down the use and nonuse into a more detailed category and addresses this issue again. Regardless of the internal mechanisms, this finding implies that thickets of nonuse patents may reach a natural equilibrium as the field of technology becomes more populated with component technologies. Of course,

whether patents are commercialized or not may not affect the costs of innovation for non-patent holders and the entry conditions into the technology markets or product markets based on the technology. Nevertheless, from a social point of view, thickets composed of used patents may be better than the thickets composed of nonuse patents.

Regime of appropriability is not exogenous. In addition, the study shows that the impact of component familiarity on commercialization is stronger for complex technologies.

We also argued that the patented inventions from capital-intensive firms are less likely to commercialize because of the presence of alternative competitive advantage, progressively increasing organizational rigidity with size, and larger protective value of patents than the benefits from commercialization. Our empirical results drawn from a U.S. inventor survey support these hypotheses. However, this result should be cautiously interpreted because we cannot clearly see just from this analysis whether the underlying mechanisms are related to switching costs, threat of cannibalization, or more filing of asset-protective patents. The mechanisms will be clearer in the following analyses of this study in which we look at the impacts of this construct on different modes of use and nonuse.

PART II. DETERMINANTS OF ORGANIZATIONAL PATHS OF COMMERCIALIZATION PROCESSES

CHAPTER 6. Introduction to Part II

Technological innovation combines inventive processes with commercialization processes (Afuah, 2003; Roberts, 1988). While they are often perceived as equivalent, they are, indeed, very different (Schumpeter, 1942). Numerous new elements not considered during the inventive processes (such as profitability, manufacturing efficiency, marketing strategy, and competitive environment) now emerge when the inventor thinks about commercialization. For example, profitability, manufacturing efficiency, ease of integration with exisiting facilities and skills, marketing strategy, and competitive environment become probably more important than technological superiority itself in the commercialization stage. To complete innovation, commercialization is essential. The innovator can choose different commercialization strategies. One of them is to decide whether to integrate downstream commercialization processes into internal capabilities or to seek alternative paths across firm boundaries. The most prominent external commercialization path is to license inventions and collect royalties. In this era of patent explosion and increasing importance of technology for firms' competitiveness, the external paths of commercialization have important implications for firms' competitiveness and economy as a whole. Also, studying factors affecting the choice between organizational paths has implications on the profitability of innovation and the technology strategy of firms.

Teece (1986) suggested that the profit from innovation was not necessarily appropriated by the innovator but may accrue to the imitator or the owner of complementary assets depending on the maturity of technology, regimes of appropriability, and the need, ownership, and characteristics of complementary assets. Recent literature about licensing endorses a part of Teece's arguments by empirically showing that the strength of patents (Arora and Ceccagnoli, 2006; Gambardella, Giuri, and Luzzi, 2007; Gans, Hsu, and Stern, 2006; Kim and Vonortas, 2006) and the ownership of complementary assets (Gambardella, Giuri, and Luzzi, 2007) are important predictors for licensing propensity. The above-mentioned empirical studies (especially licensing studies) heavily depend on TCE and partly build on the resource-based (or dynamic capabilities) view of a firm. In this study, we build on and further these two theories in the context of innovation commercialization. In addition, we attempt to illuminate different organizational trajectories of commercializing patented inventions through the theoretical lens of the knowledge network and open innovation.

In the context of firm innovation, TCE argues that firms tend to internalize innovation rather than externalize it through the market mechanism when the appropriability hazard (Oxley, 1997, 1999) of market transaction increases. One key policy instrument to reduce the appropriability hazard in transacting patented inventions is to strengthen the patent protection. The strength of patent protection is usually regarded as working at the national or industry level but also arguably can be used at the patent (Gambardella, Giuri, and Luzzi, 2007) or firm (Arora and Ceccagnoli, 2006) level. Teece (1986) argues that the rent from innovation accrues to the holder of complementary assets such as

manufacturing, sales, and/or distribution capability when an invention requires such assets for commercialization. Therefore, this argument predicts that if a firm is already equipped with complementary assets, the firm prefers internal to external exploitation of the invention. This study re-examines these arguments using multi-level and detailed data.

In the KBV of a firm (Barney, 1991; Conner and Prahalad, 1996; Kogut and Zander, 1992; Peteraf, 1993), when the firm rather than the market can provide the more valuable and "opportunism-independent knowledge," firms should prefer to produce knowledge internally rather than procure it in the market independent of transaction costs. This study tests this argument in the context of innovation commercialization. Particularly we argue that as an invention fits more tightly with the firm's existing technological strength, the invention is exploited either internally or for pure defense rather than licensed.

Finally, this study attempts to test theoretical implications from the open innovation and innovation network perspectives against commercialization decision. Particularly, we argue that the sources and strength of knowledge during the invention process predicts its use. Building on network embeddedness arguments (Powell, Koput, and Smith-Doerr, 1996; Uzzi, 1997) and the exploration-exploitation arguments (March, 1991; Rothaermel and Deeds, 2004), we develop hypotheses linking the knowledge and collaboration during the invention process to the use of its outputs.

Previous innovation surveys such as the Yale survey of 1983 (Levin, 1988; Levin, Cohen, and Mowery, 1985; Levin et al., 1987), the Carnegie Mellon survey of 1994 (Cohen et al.,

2002; Cohen, Nelson, and Walsh, 2000, 2002), the recent PatVal-EU survey in Europe (Gambardella, Giuri, and Luzzi, 2007; Giuri et al., 2007), and the Community Innovation surveys in Europe have provided lots of valuable insights on the innovation. We plan to use our inventor survey to expand on this tradition.

CHAPTER 7. Theory and Hypotheses

The main research question of this study is to examine how and why patented inventions are put into different uses. There is very little research that comprehensively examines the different modes of use of patented inventions. Most innovation research regards the patents themselves as the proxy for the innovation. The licensing literature (Arora and Ceccagnoli, 2006; Gambardella, Giuri, and Luzzi, 2007; Kim and Vonortas, 2006) focuses on the rate and propensity of licensing without considering the other modes of use. The limited literature about the strategic uses of patents either heavily depends on a single-industry perspective (Hall and Ziedonis, 2001; Ziedonis, 2004) or provides a limited explanation about the mechanisms (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000).

In this study, we depart from Teecian framework on innovation strategy of firms but enrich and articulate it with the recent development of innovation studies. In particular, we attempt to incorporate TCE, knowledge-based view, open innovation, and network perspectives into a coherent and comprehensive theory on commercializing patented inventions.

7.1. Schumpeter and Teece

In *Capitalism, Socialism and Democracy,* Schumpeter emphasized the role of monopolization in the innovation. A monopoly (or a large firm in more loosely defined terms) in the world of *Capitalism, Socialism and Democracy* has a discriminating role in both precondition and aftermath of innovation. As a precondition, he pointed out as the relative advantage of a large firm “the sphere of influence of the better [good]” (Schumpeter, 1942, p. 101) and good financial standings. As a result of innovation, a firm will enjoy a transient monopoly state caused by imitation lag. Therefore, in this Schumpeterian world, “perfect competition is and always has been suspended whenever anything new is being introduced” (p. 105). Of course, these capability and appropriability advantages of large firms in innovation can be offset by organizational rigidity stemming from bureaucratic control structures (Nelson and Winter, 1982; Schumpeter, 1942). Indeed, in his earlier work, *The Theory of Economic Development,* Schumpeter himself argued that innovation was driven by entrepreneurs (Schumpeter, 1934). Some scholars call this early emphasis of Schumpeter on small firms as Schumpeter Mark I and the later emphasis on large firms (or monopoly) as Schumpeter Mark II (Kamien and Schwartz, 1982; Malerba and Orsenigo, 1995; Nelson and Winter, 1982). The Schumpeterian hypotheses urged lots of researchers to look at the relationship between market structure (or firm size) and technological progress (see the following reviews and references therein: Kamien and Schwartz, 1975; Scherer and Ross, 1990).

The Schumpeterian hypothesis had been extensively tested during the 1960s through the 1980s. As neatly summarized by Cohen and Klepper (1996b), the consistent findings in these early studies support that R&D investment increases with firm size, although not disproportionately, but innovation output, mostly measured using patent counts, decreases disproportionately as the level of R&D or firm size increases. The underlying arguments that a large firm does more innovation consider both demand and supply aspects. To summarize these arguments, first, a larger firm, which is defined as a firm producing a larger amount of output, has less unit cost of R&D ("cost-spreading effect") than a smaller counterpart (Cohen and Klepper, 1996a, 1996b). On the supply side, a larger firm will have more lump-sum funds to invest in R&D. More R&D will diversify the research portfolio and spread R&D risks into several parallel projects to raise the odds of success. A larger investment in R&D constitutes a larger R&D team that is composed of supposedly better specialized personnel or better divides the R&D labor force to raise its capability. As a consequence of this scale economy of R&D investment, a firm investing more in R&D will have an advantage in research portfolio, R&D risk spreading, efficiency of R&D teams, and absorptive capacity. Besides R&D diversity/specialization, a larger firm enjoys an operational advantage through better vertical integration and specialization (Teece, 1986).

A huge volume of literature that has tested the Schumpeterian hypotheses does not converge to an undisputable conclusion. One reason for this inconclusiveness is probably because aggregate units such as firm or industry could not effectively capture the complex and heterogeneous activities of innovations carried out under and across firms

and industries. Firm size alone, for example, cannot appropriately capture the heterogeneous innovation activities performed by two different firms of the same size. Moreover, innovative capability and activities of the contemporary firms are not necessarily bounded by firm or industry boundary, but interlinked to outer capabilities by research collaboration, strategic alliances, or technology licensing. Therefore, we need to unpack what is going on under firms in order to better understand innovation.

Teece (1986), among others, developed a quite useful framework to analyze the mechanisms by which firms commercialize their inventions. In order to explain why many innovators fail to make a profit from innovation, he presents a simple model composed of three actors (innovator, follower/imitator, and the owners of co-specialized assets[29]) and two alternative strategies of the innovator (integrate or contract out[30]). In this zero-sum type game, he then argued that a choice of strategy (integrate or contract out) should determine to whom between innovator and follower the profit from innovation accrues. A choice of strategy is conditioned on three key factors: dominant design paradigm of technology, regimes of appropriability, and complementary assets. The latter two factors have been examined recently in lots of business strategy and innovation studies that show that they are indeed valid constructs affecting outcomes and processes of innovation. Teecian framework is especially relevant to this work in that it directly attempts to explain the reasons the innovator selects a particular strategy between two alternatives: internal and external commercialization. Teecian framework was further

[29] He stated that "[i]f there are innovators who lose there must be followers/imitators who win" (Teece, 1986, p. 286).
[30] In a later revision (Teece, 2006), Teece partially addressed an intermediate strategy: strategic alliances.

refined by Gans and Stern (2003) and applied to the context of new technology-based entrepreneurs.

7.2. Technology Uncertainty and the Costs of Market Transactions of Technology

TCE assumes a bounded rationality of economic agents and the impossibility of writing a complete contract ex ante. In this incomplete world of contracts, it is almost impossible to fully specify, ex ante, all the activities of the contracting parties that can affect the distribution or level of outcomes. Therefore, the contracting parties (e.g., manufacturer and supplier) will have incentives to behave opportunistically to take a larger share of the quasi-rents resulting from the contract. A typical form of opportunistic behavior is "hold-up," as emphasized in the TCE literature. TCE suggests that, in the situation where the manufacturer expects high chances of hold-up by suppliers, it would choose to integrate supplier capacity under its authoritative control because the authoritative control reduces opportunistic behavior and saves transaction costs if production costs of alternative organizational forms are equal. TCE literature contends that asset specificity, uncertainty, and complexity should be closely related with the ex post opportunistic behavior (Klein, Crawford, and Alchian, 1978; Williamson, 1991). When manufacturing assets are specific to a certain firm, the alternative uses of those assets are limited and the impacts of hold-up will increase. Other than asset specificity, two attributes regarding an asset or a contract affect the risk of opportunistic behavior. When an asset or a contract includes more *uncertain* or *complex* components, there will be more chances that a contracting

party exploits this uncertainty or complexity for his own benefits (Klein, Crawford, and Alchian, 1978; Williamson, 1991). TCE predicts that the contracting hazards stemming from uncertainty or complexity would suppress the transaction and promote more authoritative control. The elevated contracting hazards can be avoided in two ways: 1) ex ante by stipulating the contract for every possible contingency or 2) ex post by increasing the level of vigilance in monitoring contract misbehavior. However, because of bounded rationality and asymmetric information, both measures increase the transaction costs (Arrow, 1969; Williamson, 1979). Furthermore, uncertainty or complexity makes it harder for contracting parties to reach an agreement in negotiation. Therefore, a firm would need more authoritative controls and choose to integrate rather than contract when a contract involves a higher degree of uncertainty or complexity. Empirical studies consistently support TCE prediction in that the higher level of asset specificity, complexity, or uncertainty the more authoritative a governance structure would be (see a review by Lafontaine and Slade, 2007 and references therein).

In the innovation context, while a huge volume of literature about the strategic alliance tests the impact of transaction costs on the governance structure of alliance agreements, only a few studies examine how TCE predictions affect vertical integration of innovation outputs. The licensing research examines the rate of licensing, a less hierarchical mode of innovation commercialization, in relation with transaction cost variables such as the strength of patents or the ownership of complementary assets. However, it does not directly test the market versus hierarchy because the counterpart of licensing tested in the literature usually includes non-licensed inventions that may include nonused ones as well

as internally commercialized ones. As predicted by TCE, as asset specificity, uncertainty, and complexity increase, more hierarchical governance structure is chosen in alliance, R&D procurement, or invention commercialization. In the innovation context, many studies test the effect of the strength of appropriability regime on the governance structure instead of separately testing the effect of elements comprising appropriability hazards. Aside from Oxley's test of geographic uncertainty, Veugelers and Cassiman's test based on the Belgian Community Innovation Survey shows the opposite direction as predicted by TCE, i.e., the lower uncertainty or lower appropriability hazard is related with more hierarchical structure ("make" rather than "buy").

In the context of commercializing patented inventions, asset uncertainty and contractual complexity come from several different sources. We will discuss two of them: characteristics of technology and the strength of intellectual property rights.[31] The existing literature has almost exclusively focused on the effectiveness of patent protection (Anand and Khanna, 2000; Arora and Ceccagnoli, 2006; Fontana, Geuna, and Matt, 2006; Gans, Hsu, and Stern, 2002, 2006; Gulati and Singh, 1998; Nagaoka and Kwon, 2006; Oxley, 1999; Veugelers and Cassiman, 1999). The literature argues that strong patent protection should reduce a buyer's post-contract haggling and lower the chances of a seller's unexpected losses from the market contracts. Therefore, there will be a higher chance of market transaction of technology when patent protection is stronger. Gans, Hsu,

[31] Another source of contractual uncertainty and complexity will be related to the relative positions of firms in the product market or industry structure. Also, the history of dyadic relationship (including trust) between the contracting parties will affect the level of the contracting hazard. We recognize that these factors may be important in determining the contracting hazard. However, we do not consider them in this study because they are much more complex to analyze and require a data set of very different nature from what is available to us.

and Stern (2006) found that licensing propensity significantly increases with the granting of formal intellectual property rights. In cross-licensing agreements among Japanese firms, Nagaoka and Kwon (2006) found that licensing agreements for transferring patented inventions are more likely to occur than licensing agreements for transferring only know-how. Some other studies use a strong protection regime at the national level (Oxley, 1999), the industry level (Anand and Khanna, 2000; Gulati and Singh, 1998), or at the firm level (Arora and Ceccagnoli, 2006; Veugelers and Cassiman, 1999). All of these studies consistently found that weaker protection regimes were associated with more authoritative control of either upstream or downstream assets.

At last, we reach our main arguments: What are the meanings of technological uncertainty and complexity and how they are related with contracting hazards in the context of commercializing patented inventions? Technological uncertainty refers to the variability of its applicability and utility. Analogizing technological progress to Kuhnian explanation of scientific progress, Dosi (1982) argues that, once a technological paradigm is established, most technological progress will take a similar pattern, or, according to his words, follow a prescribed trajectory set by the paradigm. Therefore, technological change in a paradigmatic (or "normal") stage in the technology development cycle will be incremental and, hence, less uncertain. Despite some differences in nuance and language, linkage between the evolutionary path of technology and uncertainty is firmly established in the literature (Abernathy and Clark, 1985; Anderson and Tushman, 1990; Tushman and Anderson, 1986; Utterback, 1994). Fleming (2001) and Fleming and Sorenson (2001) empirically show that variability of utility of technologies indeed

decreases (to a certain degree in Fleming (2001)) with the size of recombinant search space of technological components. When applicability or utility of a technology is not clearly known to the potential buyer of that technology, he would worry about overpaying for that technology. On the other hand, the owner of the technology would worry about the underestimation of the value of technology. Either underestimation or overestimation would make it harder for contracting parties to reach an agreement. Certainly, contracting parties can reduce this uncertainty if they can appraise the future value of technology correctly. However, the appraisal process itself will also incur additional costs of information processing or in building a proper level of capacity (Cohen and Levinthal, 1990). Combining TCE with the evolutionary explanation of technology, we finally reach the following hypothesis:

Hypothesis M1. As technological components become more familiar, the propensity to externally commercialize a patented invention will increase.

7.3. Strong Internal Position for Complementary Assets and the Prospect of Internal Synergy

Teece (1986) asserts that specific assets complementing core technological know-how (e.g., patented inventions) are a critical element determining profitability of innovation. In particular, he argues that, in a weak appropriability regime, profit from an innovation accrues to the innovator, imitator, or holder of complementary assets depending on two

conditions: 1) the level of specialization of complementary assets that is required for commercialization, given the first condition, and 2) how strong each player holds a position in the complementary assets relative to each other. Simply put, the Teecian innovator would internalize downstream assets for commercialization (rather than procure them in market) in the following cases: 1) where the critical complementary assets are available in-house; 2) if they are not available in-house and the complementary assets are specialized, where a) cash position is OK for building them in-house and b) the innovator is disadvantageously positioned in commissioning complementary assets compared to imitators or competitors. Therefore, if we assume that most inventions would require a certain degree of specialized complementary assets (including manufacturing, service, distribution, or complementary technology) for commercialization (Roberts, 1988), a strong position of the innovator for the complementary assets would predict in-house integration of these assets (Case 1). The second case addresses such inventions where the innovator has a weak internal position of the complementary assets. Inventions in this case will be either vertically integrated or contracted out for their necessary downstream assets for commercialization depending on financing capability and the assets position of the innovator relative to imitators or competitors. This case is not a main focus of the current study.

Teece's prediction about strong internal complementary assets position and vertical integration is supported also by TCE and KBV. In TCE, when the downstream assets are difficult to redeploy to other uses or other users, the provider of such assets will be easily attracted to using this tight bonding toward his own benefits by, for example, holding-up

or threatening the manufacturer (Williamson, 1991). According to TCE, the manufacturer would respond to this potential loss by increasing authoritative control over the assets and, therefore, would choose vertical integration rather than market contract. In KBV, the focus is placed on internal synergy between activities. If a firm expects more synergistic effects by combining activities internally, then it will integrate those activities. KBV argues that fitness among different activities, complexity, tacitness, and learning effects increase internal synergy (Conner and Prahalad, 1996; Kogut and Zander, 1992, 2003). This is similar with a resource-based view in that it regards organizational routine, which contains most elements mentioned above, as one of valuable, non-imitable, and rare resources (Barney, 1991).

To clarify this point in the context of technological invention and its commercialization, consider the following examples. When an invention is an improvement on the existing products or processes, it would be more likely than an invention for new products or processes to link to the existing manufacturing facility, skills, or the site of factory. In TCE terms, the improvement invention will contain more site specificity, physical specificity, and human-asset specificity (Williamson, 1981, 1991) and, therefore, will be more likely to be internally commercialized. Similarly, in KBV terms, a firm would expect more internal synergy by integrating its downstream commercialization efforts for the improvement invention because of the fitness of this invention with the existing skills and facilities. Tushman and Anderson (1986) dichotomize types of innovation by the degree to which an innovation makes the existing competences obsolete. When an innovation creates a new product or process, such innovation will require a new set of

skills, processes, and assets. On the other hand, when a technological invention results in improvement in the existing product or process, firms may be able to use existing competence (or complementary assets required to commercialize that invention). Thus they define technological discontinuities (or innovations) that create or substitute for an existing product or process as "competence-destroying" and technological discontinuities that improve an existing product or process a "competence-enhancing" innovation. Indeed, they found that competence-enhancing innovations were made more in the existing firms. Arora, Fosfuri, and Gambardella (2002) found that about a third of all chemical licensing was made by specialized chemical engineering firms that lacked manufacturing facilities. Arora and Ceccagnoli (2006) also found that firms lacking specialized complementary assets were more likely to license their invention and less likely to internally commercialize it.

For another example, consider the inventions made by manufacturing units. On the same line of argument as the previous example, this kind of invention would be more tightly coupled with asset specificity and the prospect of internal synergy. Hence, we predict that the inventions made by manufacturing units will be more likely than, for example, inventions made by independent R&D units, to internally commercialize. The argument presented here is summarized into the following hypothesis.

Hypothesis M2. A patented invention having a strong internal complementary assets position will be more likely to be internally commercialized.

7.4. Collaboration, network embeddedness, and technological opportunity

In the previous sections, we discussed two theoretical approaches relevant to the make-or-buy decision of commercializing patented inventions. While TCE focuses on comparisons of the management costs with the contractual hazards in a dyadic relationship, KBV emphasizes synergistic effects that would not be produced by contractual relationships but would be possible by integrating complementary activities internally. The innovation network and organizational learning perspectives agree with KBV in that the transaction costs should be only a partial explanation of the choice of governance structure and that some complementary combinations not attainable through market relationships should be an important dimension to determine the choice of governance structure. A critical difference from KBV, however, is found in the stretch of organizational boundary over which such synergistic effects happen. While KBV confines the boundary of complementary combination within a firm, the innovation network perspectives extend it over the networks of firms. Both TCE and the network perspectives focus on the relationships with external entities. However, while TCE focuses on how the attributes of the relationship work as a potential risk, the network perspectives focus on how the relationship can generate some positive benefits otherwise impossible. In this sense, we basically agree with Jacobides and Winter's contention that "TCE focuses on the conditions of exchange, to the neglect of the conditions of production" (Jacobides and Winter, 2005, p. 398). However, there is a more fundamental

aspect about the roles of the networks in innovation and economic behavior beyond the problem of avoidance of negatives or production of positives.

The attacks were initiated by sociologists whose main concerns are placed in understanding how social relations affect individual behavior. Granovetter (1985) criticizes that economic arguments ignore the social context and the history of interpersonal relationships outside of which human actions cannot be formed. As a consequence, he contends that economic arguments, whether they are neoclassical or new institutional, are either *over-socialized* or *under-socialized.* In his view, networks are omnipresent (they exist even in hierarchy as well as in markets) and human actions are "embedded in concrete, ongoing systems of social relations" (p.487).

Powell (1990) basically agrees with Granovetter on the importance of social structural embeddedness in determining economic exchanges and on the limitation of arraying economic exchanges on the market-hierarchy continuum. Nevertheless, he argues that "certain forms of exchanges are more social" (p.300) and submits that there is an empirical merit to distinguish the network form as a distinct governance structure from either market or hierarchy. Powell identifies several key distinct characteristics of each of three governance forms. The network structure is dominated by a norm of reciprocity and reputational concerns while hierarchy (market) is dominated by administrative fiat or supervision (haggling or court enforcement). Also, information communicated over networks is richer than information obtained in the market and "freer" than information circulated in a hierarchy. Therefore, Powell contends that "[n]etworks, then, are

especially useful for the exchange of commodities whose value is not easily measured" (p.304). On this line of argument, a network form of organization is defined as "any collection of actors ($N \geq 2$) that pursue repeated, enduring exchange relations with one another and, at the same time, lack a legitimate organizational authority to arbitrate and resolve disputes that may arise during the exchange" (Podolny and Page, 1998, p. 59). This definition includes formalized relations such as joint ventures, strategic alliances, franchises, research consortia, relational contracts, and outsourcing agreements, but also research collaborations, informal information exchange (von Hippel, 1994), repeated supplier-customer transactions, and other non-codified forms of regularized interactions with external organizations.

Powell further argues that know-how, the demand for speed, and trust are critical to forming networks. The exchange of know-how, which, according to Powell, is characterized by tacitness and embodied in a highly mobile skilled labor force, is more suitable for network forms because of the lateral structure of communication and mutual obligation of networks. Dynamic adaptability of a network structure that is mostly based on the ability of information dissemination and interpretation is more suitable for the competition based on fast innovation capability. Finally, the common backgrounds that may stimulate trust among actors contribute to forming networks. In addition to these factors, needs for legitimacy and status that may be derived from network affiliation is listed as a factor affecting network formation (Podolny and Page, 1998; Stuart, Hoang, and Hybels, 1999). The key testable implications of embeddedness, therefore, are that network forms of organizations are more preferred when the above-listed factors are

prominent ceteris paribus and, consequently, that network forms of organizations result in unique opportunities and constraints not predicted by standard economic explanations (Uzzi, 1996).

It is well known in the literature that networks affect the outcomes of innovation (Afuah, 2000; Dyer and Nobeoka, 2000; Gulati and Higgins, 2003; Gulati and Sytch, 2007; Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Deeds, 2004, 2006; Shan, Walker, and Kogut, 1994). Furthering these arguments, here we discuss how the types of networks formed during the explorative stage of innovation (i.e., invention stage) affect the organizational trajectory of the later stage of innovation (i.e., commercialization stage).

Network forms are known to be conducive to exchange of commodities of uncertain value or know-how that is tacit and embodied in a mobile labor force (Powell, 1990). As discussed below for external sources of knowledge, networks established during the invention process would provide more technological opportunities that can be commercially exploited. This technological advantage from networks, therefore, would raise a chance for commercial exploitation, either internally or externally of the invention. Additionally, networks would benefit firms by providing more market opportunities. For example, a participant joining the network relationships can either be a potential buyer of the invented technology or signal the competency of the technology to the markets (Podolny and Page, 1998; Stuart, Hoang, and Hybels, 1999). Also, a possible trust relationship formed through earlier explorative ties may be maintained through the ties in

the later stage of commercialization. Empirical studies on alliance and organizational learning found that networks formed during the explorative stage of innovation would indeed induce the exploitative networks (Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Deeds, 2004).

Then we give attention to qualitative differences among the collaborations according to different characteristics of partner types. Below, we extensively discuss the characteristics of external knowledge by its sources and its impact on commercialization. Similar to this discussion, collaboration with industrial partners would favor the internal commercialization path if only knowledge and technological aspects are considered. However, we claimed above that demand opportunity in markets for technology and embeddedness structure should affect the commercialization path. To clarify this effect, we divide industrial collaboration into two types based on the relationship of partner firms with the focal firm. The vertical collaboration includes partners in vertical relationships, such as suppliers or customers. The horizontal collaboration includes partners in horizontal relationships with the focal firm, such as competitors, a firm in the same industry, or an unrelated firm in other industry.

Partner firms in vertical relationship are assumed to be mutually dependent on the focal firm and have a relatively clearer division of labor. Several studies, indeed, report that collaboration with suppliers, competitors, or customers is critical in the success of innovation (Dyer and Nobeoka, 2000; Gulati and Sytch, 2007; Rothwell et al., 1974; von Hippel, 1988). The same arguments we made for external industrial knowledge can be

applied to this type of collaboration. Additionally, mutual gains in learning and technological fitness achieved through inventive collaboration will be better exploited through internal commercialization. In other words, the closely aligned capabilities extended over dependent firms would not be properly evaluated nor transferred in the market for technology. This argument leads to the following hypothesis.

Hypothesis M3a. A patented invention developed through collaboration with firms in vertical relationships will be more likely to take internal commercialization paths.

On the other hand, firms in horizontal relationships are assumed to have competing, but possibly complementary, technologies. Collaboration among these firms will bring forth higher chances of demands for the technology in the markets for technology. Also, as the network embeddedness arguments say, firms will receive mutual benefit by maintaining ongoing trust relationships that can be attained through, in our case, licensing the invention. In addition, because know-how flows in both directions over the collaboration network, the collaborating partner, who may be a potential competitor in the product market, would have achieved a similar level of technological knowledge. Therefore, attempts to block such potential competitors from accessing the technology would not be effective. This effect will be particularly prominent in cross-licensing but also in unidirectional licensing. As Arora and Fosfuri (Arora and Fosfuri, 2003; Arora, Fosfuri, and Gambardella, 2002) argued, while the rent dissipation effects will be minimal in this case because knowledge transfer would have already occurred during the inventive collaboration, the revenue effects would be totally lost unless the patent is provided for

(cross-)licensing. In summary, based on all these reasons, we predict that horizontal collaboration will incentivize a firm to take an external commercialization path.

Hypothesis M3b. A patented invention developed through collaboration with firms in horizontal relationships will be more likely to take external commercialization paths.

Furthermore, network embeddedness arguments suggest that social relations can mitigate high transaction costs. For example, a collaboration network during the invention process encourages the network members to exchange formal and informal knowledge and, moreover, provides them opportunities to develop trust in each other through repeated interaction. When technology is highly uncertain, better understanding of the technology through knowledge exchange will lower the uncertainty. Furthermore, trust relationships will ameliorate the opportunistic behavior problem. This suggests a testable hypothesis: that transaction cost problems should have less of an impact in the presence of relational contracting or networks. In combination with the previous arguments about impacts of horizontal collaboration on external commercialization paths, we formulate the following hypothesis:

Hypothesis M3c. The effect of horizontal collaboration on the propensity to take external paths of commercialization will be stronger for the inventions whose technological uncertainty is higher.

7.5. Nature of External Knowledge

Open innovation arguments (Chesbrough, 2003; von Hippel, 1988) emphasize the importance of external ideas and external paths to market in innovation. This "new breed of innovation" (Chesbrough and Appleyard, 2007, p. 57) depends on various sources of knowledge including universities, suppliers, customers, and even competitors. In the open innovation era, a firm puts more weight on knowledge brokerage than knowledge creation (Chesbrough, 2003; Cohen and Levinthal, 1990). Also, due to the risk as well as the opportunity involved in open innovation strategy, the roles of intellectual property rights have increased, although the use of intellectual property in these cases may be less about exclusive in-house use and more as a means of exploiting external opportunities and of facilitating the (compensated) dissemination of the technology to others (including potential competitors).

The ability to evaluate and assimilate external knowledge is a critical component of innovative capabilities of contemporary firms (Chesbrough, 2003; Cohen and Levinthal, 1989, 1990; Laursen and Salter, 2006; Rigby and Zook, 2002; von Hippel, 1988). Cohen and Levinthal (1989, 1990) argue that extra-industry knowledge provides technological opportunities that a firm can absorb and transform into commercial ends by investing in internal R&D. Organizational learning literature claims that exploiting external knowledge (or distant search or explorative search) would lead to better innovative performance because it provides a larger pool of recombinant technology components and the possibility of larger variations (Katila and Ahuja, 2002; Laursen and Salter, 2006;

March, 1991). Katila and Ahuja (2002) and Laursen and Salter (2006) empirically show that the scope of external search, either measured by the ratio of new citation in firm patents (Katila and Ahuja) or the number of external knowledge channels exploited by a firm (Laursen and Salter), predicts better innovation performance of firms.

According to Katila and Ahuja (2002), external channels of knowledge may enlarge the pool of technological knowledge by adding new distinctive variations (or "variation effects"). As the pool of knowledge gets more diverse, the chances to solve existing technological problems increase (up to a certain point, though). On the other hand, external knowledge will simply add technological elements that can be exploited in the recombinant search process (or "size effects") (Fleming, 2001; Katila and Ahuja, 2002). Either variation effect or the size effect, however, would have a saturation point (beyond which the quality of outcomes of innovative activities would decrease) because an economic agent would have a limited information processing ability. Fleming and Sorenson (2001) provide empirical evidence that the performance of an invention (as measured by the forward citation counts) increases at a decreasing rate and then decreases at an increasing rate as the number of technological components (as measured by the number of technology sub-classes) increases.

Cohen and Levinthal (1989, 1990) argue that the amount of effort for a firm to exert to absorb external knowledge should be ordered by the degree to which the knowledge is "targeted." According to them, absorbing less targeted knowledge, which is typically associated with a university or a government, would require more internal R&D than

targeted knowledge, which is typically associated with industry partners, such as suppliers. Here we focus on the difference of nature between two types of external knowledge: 1) knowledge originating from suppliers or, more broadly, industrial sources, including users and competitors and 2) knowledge originating from public domains. As Cohen and Levinthal assumed, industrial knowledge is not only targeted to commercial application but also likely to have more local, contextual, or industry-specific elements, such as organizational routines, informal know-how, or product ideas (von Hippel, 1988). Here we define industrial knowledge more broadly including knowledge from competitors and users as well as suppliers. On the other hand, public sources of knowledge are closer to basic science in nature, characteristics of which are more global, general, or broadly applicable. They will be less targeted to a particular commercial application and tend to be detached from a particular industry practice. As a consequence, public sources of knowledge will take longer or require absorptive capacity (which can be built by an additional investment on top of the ordinary product development process) to absorb and transform into commercial application. An empirical study of the robotics industry by Katila (2002) shows that extra-industry knowledge sources (such as universities, government labs, or different industry) takes more time to be transformed into new product development than intra-industry knowledge sources. Fleming and Sorenson (2001) find that the higher the level of interdependency of technological components included in a patent, the more people use the patent as measured by the forward citations count.[32]

[32] Indeed, they find that the level of technological interdependency is in inverted-U relationship with the forward citations count.

In summary, external industrial knowledge would have different attributes from external public knowledge and, therefore, their impacts on commercialization would diverge. An invention that has exploited more external *industrial* knowledge would be more suitable for internal commercialization strategy for the following reasons: First, knowledge required for the downstream commercializing process after developing core inventions would fit better with industrial sources of knowledge. A new product development process incorporates lots of problem-solving efforts localized around a specific problem and, in most cases, routinized through the past trial-and-error experience (Carlile, 2002). For example, developing peripheral technologies, modifying existing facilities to accommodate a new invention, and training workers for new skills to run the modified facilities/process follow the invention process. The characteristics of industrial sources of knowledge, as described above, fit better with this process and, therefore, save the innovator efforts for downstream commercialization. In addition, on a similar line of arguments we made for the complementary assets and asset specificity, a firm that has already internalized these valuable and hardly imitable capabilities for commercialization during the invention process would benefit more by taking an internal path to commercialization.

Second, while internal gains from learning will be greater for industrial sources, the losses that may accompany an external commercialization strategy will be smaller for public sources. This will incentivize a firm to choose an internal commercialization path for an invention depending more on industrial sources and an external path for an invention depending more on public sources. Lane and Lubatkin (1998) found that gains

in inter-organizational learning increase when there are similarities in the knowledge base, governance structure, and dominant logic among teaching and learning organizations. In Cohen and Levinthal's (1990) studies, additional exploitation of knowledge from suppliers actually results in a lower level of internal R&D. Based on their findings, we postulate that a firm would have gained more in learning from industrial partners because of a greater level of similarity between them. This argument reinforces the first argument. This characteristic also makes it more difficult and more expensive for the gained knowledge to be transferred to others, which makes an external path to commercialization harder to adopt.

Third, an invention depending more on public sources will take an external commercialization path. Knowledge from public domains tends to carry less immediate commercial value and be generally disclosed to a wider community and less embedded in a particular practice than industrial knowledge (Jensen and Thursby, 2001; Owen-Smith, 2003). This characteristic reduces transaction costs of trading the technology in the markets. Also, the negative impacts of spillovers on the other technologies owned by a firm that might be caused by market transactions of the technology will be lower than transferring a technology based on only internal knowledge. Therefore, more dependence on external public knowledge will lower the barrier and risk for an external commercialization path. In other cases in which knowledge has been transferred directly from a governmental organization, often the government organization forces the recipient firm to license the patented technology to other parties in need of the technology. This

practice will also increase the chances of inventions dependent more on public knowledge taking an external commercialization path.

Finally, similar to the first two arguments but in more prospective nuance, we argue that an invention dependent more on external industrial knowledge would be prone to take an internal path to commercialization because of the prospect for a greater level of internal synergy. This argument builds on and extends the KBV of a firm. KBV identifies a firm as having a "knowledge creation function" (Kogut and Zander, 1992; Nonaka, Toyama, and Nagata, 2000) and claims that a firm decides to internalize technology development when the technology is assessed to create internal synergy, regardless of the level of the appropriability hazard (Conner and Prahalad, 1996). Then which type of knowledge would generate, as a firm expects, more internal synergy? As we described above, industrial knowledge generally contains more contextual and industry-specific elements. Also, it would be well-aligned to the firm's existing practice but still include novel elements to the firm (otherwise the firm would not need to use external knowledge). A firm would expect internal synergy by integrating this knowledge further into downstream assets (Lane and Lubatkin, 1998). Conner and Prahalad (1996) point out knowledge-substitution effects. Simply put, when there is a need for combining knowledge sufficiently complex and tacit, authoritative control by several experts will be much more efficient than negotiation and voluntary coordination among less-informed agents. Thus, a firm would receive more gains in efficiency by integrating complex and tacit knowledge, which is characteristic of industrial knowledge.

Hypothesis M4a. The higher the contribution of external *industrial* knowledge to an invention, the higher will be the propensity to *internally* commercialize the invention.

Hypothesis M4b. The higher the contribution of external *public* knowledge to an invention, the higher will be the propensity to *externally* commercialize the invention.

CHAPTER 8. Data and Measures

8.1. Data

The estimation sample is based on the GT/RIETI survey and supplementary data sources including the PATSTAT, USPTO database, and COMPUSTAT as described in CHAPTER 5. Out of 1,919 valid responses, 1,807 cases are from firms. After deleting listwisely the cases that have missing values on our covariates, we have 1,226 complete cases for estimation.

8.2. Variables and Measures

8.2.1. Dependent Variables

The GT/RIETI survey asks inventors how they are commercially using their patented inventions and, if not used, the reasons why they do not use them. We identify a patented invention as commercially exploited ("any use") if it is 1) commercialized in a product/process/service by the applicant or owner of the patent, 2) licensed out or put in a cross-license deal by (one of) the patent-holder(s) to an independent party, or 3) commercially exploited by the respondent or any co-inventor for starting a new company. First, we construct a variable "any use" by coding 1 for the patented inventions falling in any of these three categories. We coded 0 for those observations who explicitly reported

that the patented invention was not used for all three commercial modes. Some answered to only some of these three questions. This affects identifying nonuse. In survey, then, we asked the reasons why a patent was not used. We regard those cases that provided valid answer to the reasons for nonuse question but only partially reported nonuse in three use questions as nonuse. Out of 1226 complete cases, 651 (53.1%) patents are reported to be used (Table 8.1).

Internal and external commercialization

The variable "internal commercialization" is coded 1 for those observations reporting that a patent is "commercialized in a product/process/service by the applicant or owner of the patent" but *not* licensed (including cross-license) *nor* commercially exploited by the respondent or any co-inventor for starting a new company.[33] Among the used patents, 74% were purely internally used. The rest of used patents are regarded as "external commercialization."[34]

[33] We excluded start-ups from university, hospitals, private and government research organizations, and individual inventors by limiting our sample to the inventor belonging to firms at the time of invention.

[34] Out of 172 patents thus identified as "external," 113 patents were also used internally. We classified them into "external" for the following reasons. First, although our question framing for internal use explicitly stated whether a patent had been used by "the applicant/owner," this may have been broadly interpreted by the respondents as including external uses. So, we guess that the proportion of actual dual use patents should be less than two-thirds. Second, even if some dual-use patents are included in external use, this will give us conservative estimates for our independent variables. So to speak, considering that we hypothesized opposite effects of our independent variables on the mode choice, if we had excluded those dual-use patents from external use, we would have had even stronger effects of these variables on external use. Finally, we may have overestimated the effects on "internal use" by excluding dual-use. However, this may not cause a problem because we hypothesized indeed for purely internal use.

Table 8.1 Modes of commercial use and nonuse (N=1226)

Mode	Cases	percent
Any use	651	53.1
Internal commercialization	482	39.3
External commercialization	169	13.8
- Licensed	122	10.0
o cross-license	30	2.4
- New firm	63	5.1
o license & new firm	16	1.3

8.2.2. Explanatory Variables

Measures for complementary assets

We capture complementary assets position using two survey measures: 1) whether an inventor belongs to manufacturing unit and 2) whether the type of the invention is competence-enhancing rather than competence-destroying.

Dummy for manufacturing unit

In Teecian arguments, the complementary assets interfere with mode choice of innovation in three different points. If the invention does not require complementary assets, it is immediately commercialized by the inventor. When the invention requires complementary assets for commercialization, the degree of specialization and the ownership of those assets play a role. Empirically, it is hard to assess whether a particular invention requires complementary assets for its commercialization and how specialized those assets should be. Therefore, we assume that every invention requires a certain type

of downstream assets such as manufacturing facility and that those assets are somewhat co-specialized. An invention from a manufacturing unit is already or ready-to-be coupled with downstream co-specialized assets. The GT/RIETI Survey asks which organizational unit the inventor belongs to. Unit-manu is marked 1 if the inventor belongs to manufacturing unit and 0 for R&D unit (either independent or sub-unit attached to non-R&D function), software development, sales & marketing, and others.

Competence-destroying invention

Tushman and Anderson (1986) characterize competence-enhancing innovation as "order-of-magnitude improvements in price/performance that build on existing know-how within a product-class" and competence-destroying innovation as such innovation that "either creates a new product class … or substitutes for an existing product" (p.442). In survey, we asked a similar question whether the type of innovation was to create a new process or product or to improve an existing process or product. Using this survey question we create "competence-destroying invention" dummy variable by coding the former 1 and the latter 0. This measure does not exactly correspond to Tushman & Anderson's characterization. For example, if some new products or processes actually may build on existing competence, then the invention linked to this sort of products or processes cannot be competence-destroying. However, without further information by which we can assess whether and to what extent a particular invention substantially recycles existing skills, processes, or assets, this measure is the best proxy of competence-enhancing invention available to us. We guess that a part of competence-

enhancing invention might have been falsely classified into competence-destroying invention.

Measures for technology uncertainty

We operationalize technological uncertainty using the familiarity index of technological components following Fleming (2001).[35] The component familiarity captures the degree to which a patentee is familiar with the technological components that were used in his patent. The basic assumption is that as a technology matures (therefore, the population of technological artifacts increases), technological trajectories based on this technology become more foreseeable (Dosi, 1982). Component familiarity, as suggested by Fleming, averages the number of patents previously assigned to the same technology classes of the focal patent and applies a knowledge attenuation factor by temporal distance between the focal patent and the referred patents. He has empirically shown that component familiarity had inverted-U relationship with the uncertainty of utility of the patent as measured by the variation of forward citation counts.

In order to construct this variable, first we count the number of U.S. patents filed from 1976 to 1999 in each technology class.

[35] In this study, we focus on uncertainty and complexity stemming from the nature of technology. Whereas the strength of patents has been widely used, it is often vague in both concepts and measurement. Moreover, crucial elements that make patent protection effective are, we argue, inherited from the nature of encapsulated technology. In one sense, strong patents may refer to those patents linked to a technology in large demands. However, if such technology can be easily invented around (or there exists a viable alternative technology), then the effectiveness of patents in protecting inventor's interests should be weakened. Also, crucial parts of most cases of patent appeals or infringement law suits are related to the aspects of encapsulated technologies. Therefore, we conclude that patent effectiveness is crucially dependent on the uncertainty and complexity of encapsulated technology and that the latter is more fundamental and suitable for measuring contracting hazards in market for technology than measuring the perceived effectiveness of patent protection at aggregated levels.

Component familiarity for patent i =

$$\frac{1}{N_{C_i}} \sum_{c_j \in C_i} \sum_{\substack{all\ patents\ k\ filed \\ from\ 1976\ to\ 1999}} 1\{patent\ k\ assigned\ to\ subclass\ c_j\} \times kattenuation_k$$

Where $C_i = \{\text{patent subclass assigned to patent i}\}$,

c_j = patent subclass identifier,

N_{C_i} = number of different patent subclasses assigned to patent i.

Knowledge attenuation factor is calculated as follows,

$$kattenuation_k = \exp\left(\frac{\text{temporal distance of patent k}}{\text{time constant of knowledge loss}}\right),$$

where temporal distance of patent k=

4.5 if patent k was filed from 1995 to 1999

9.5 if patent k was filed from 1990 to 1994

16.5 if patent k was filed from 1976 to 1989

Time constant of knowledge loss is set to 5 years following Fleming (2001). We rescaled component familiarity by dividing it by 1000.

Knowledge flow measures

The GT/RIETI survey asks how importantly the various knowledge sources have contributed to the invention in 1) suggesting stage and 2) completing stage. The measure is 6-point Likert scale with 0 for "did not use," 1 for "not important," and 5 for "very important". We asked about 11 knowledge sources: scientific and technical literature, patent literature, fair or exhibition, technical conferences and workshops, standard documents, your firm (excluding co-inventors), universities, government research organizations, customers or product users, suppliers, and competitors. We take a

maximum value of answers from suggestion and completion questions and construct the following four variables.

Industry and public knowledge

We summed up importance scores of 4 external knowledge sources: scientific literature, technical conferences, universities, and government research organizations. Then, we divide the sum by 20 and construct the variable industrial knowledge which ranges from 0 for not using any external public knowledge and to 1 for fully using external public knowledge (Cronbach's alpha=0.69). The variable industrial knowledge is similarly constructed from the rest of external knowledge sources: patent literature, fair or exhibition, standard documents, customers and product users, suppliers, and competitors (Cronbach's alpha=0.66). In order to verify the structure of these two common factors we conducted a confirmatory factor analysis. The results of the analysis confirms the hypothesized latent structure as indicated by the most of the goodness of fit statistics (e.g. Chi-square pr.> 0.1511; NFI=0.9914; GFI=0.9965). A detailed description of factor analysis is provided in Appendix B.

<u>Collaboration measures</u>

The GT/RIETI Survey asks whether the focal patent was developed with inventors who belong to various external organizations and whether the focal patent was developed through formal or informal collaboration with external organizations. The survey presents 8 distinct categories for external organizations including suppliers, customers and product users, competitors, non-competitors within the same industry, other firms, universities,

government research organizations, hospitals, and other. In order to test hypothesis 4a and 4b, we classified the type of collaboration into three groups according to the nature and relationship of the collaboration partners with the focal firm. They are collaboration with 1) public organizations, 2) firms in vertical relationship, and 3) firms in horizontal relationship. Based on this classification, then, we construct three collaboration dummies. The variable "collaboration –public" is coded 1 if all reported collaboration partners fall in any type of public organizations including universities, government research organizations, and hospitals. The variable "vertical collaboration" is coded 1 if the inventor organization had co-invented or collaborated with either suppliers or customers. The variable "horizontal collaboration" is coded 1 if the inventor organization had co-invented or collaborated with competitors or other firms (i.e. non-supplier, non-customer, and non-competitor).[36]

8.2.3. Controls

Firm size

Size of firms is known be an important factor determining firms' propensity to license (Gambardella, Giuri, and Luzzi, 2007). The variable, "Large firm," is coded 1 if the inventor belonged to a large firm (defined as having more than 500 employees) at the time of invention. We used the survey responses for those observations having valid

[36] This categorization is theory-driven but also conforms to the latent factor structure. We conducted an exploratory factor analysis using tetrachoric correlations. We obtained a three-factor solution with similar structure as we described above except for one small difference. According to the factor analysis, it seems that "other firms" may better be classified into public collaboration rather than horizontal collaboration. However, this does not conform to our theoretical explanation so that we keep "other firms" in horizontal collaboration. The reliability coefficients, Cronbach's alpha, for each group range from 0.39 to 0.51, which are below the conventional cut-off, 0.7. However, this does not tell our grouping is bad because we have only two or three items in each group and, in our survey, collaboration with multiple partners are only in a rare occasion (less than 10% of cases) which result in low correlations among variables.

responses (1739 cases). For the remaining 108 cases on which there were no responses from the survey, we assessed whether an assignee firm is large or not using complementary data sources such as COMPUSTAT firm database, Patent Fee Maintenance Database of the USPTO, and company websites.

Technological capabilities of firms

We use patent stock as a proxy for technological assets of a firm. Patent stock is calculated as the number of granted U.S. patents assigned to the first assignee in the focal patent and filed before the filed year of the focal patent. Patent stock of firm i for a focal patent filed in year t is:

$$PS_{it}=PS_{i\,(t-1)}(1-\delta)$$

where δ represents the constant depreciation of knowledge which is set to 15% following the previous studies (Grimpe and Hussinger, 2008; Hall, 1990).

Similar to the way we construct the capital intensity, subsidiary firms are consolidated into their ultimate parents. Patent stock of merged and acquired firms is also consolidated into the merger. We use the PATSTAT database (April 2008 version) compiled by the European Patent Office. There are two advantages using the PATSTAT for this purpose. First, the PATSTAT provides relational tables and SQL interface for the bibliometric information of the U.S. patents which make data extraction much easier than other available data sources. Second, PATSTAT provides standard ID numbers of assignees

which corrected many small differences of spells. We further cleaned the data by manually searching and correcting the list of assignees in our sample.

R&D for base technology

This variable discriminates the business needs of the invention. Using our survey, we code 1 for this variable if the reported purpose of research is "enhancing the technology base of the firm or the long-term cultivation of technology seeds."

Proportion of basic R&D

This variable is a proxy measuring the position of the invention on basic-applied spectrum. In the survey, we asked the inventor how much effort (in percentage) he put in basic research. The other categories presented are "applied research," "design and/or development," and "technical services."

Technological value of patents

In our survey, we ask the inventor assess technical significance of her invention relative to other technical developments in her field during the year the focal patent was applied for. We code 4 for top 10%, 3 for top 25% (but not top 10%), 2 for top 50% (but not top 25%), and 1 for bottom half.

Man-month and number of inventors

We control the resources invested in the invention using two different measures. The variable "man-month" is an ordinal variable constructed from the survey question asking

“[a]pproximately how many man-months did the research leading to the focal patent require”. The answer categories are 9 levels from “less than one man-month” to “more than 97 man-months.” We take median values of each category and divide it by the maximum value to make it ranged between 0 and 1. In addition, we control the number of inventors as registered in the U.S. patent publication.

Type of innovation

Product innovation is observed to differ in some aspects from process innovation (Cohen, Nelson, and Walsh, 2000). We identified product innovation using our survey. which referenced to process innovation or mixed innovation whether or not an invention is for product innovation.

Strength of patents

We control two measures of patent strength: the number of different technology subclasses, and the number of claims. These variables are used in the previous studies as a measure of patent strength (Gambardella, Giuri, and Luzzi, 2007).

The number of different technology classes are regarded as strength of patents (Gambardella, Giuri, and Luzzi, 2007), complexity of technology, or scope of invention (Nerkar and Shane, 2007). Nerkar and Shane found a positive association of this variable with the propensity to commercialize academic inventions. The U.S. patent office assigns each issued patent to at least one relevant technology class which comprises approximately 100,000 subclasses. It periodically reorganizes the classes and updates all

the issued U.S. patents accordingly. This classification reflects a cognitive boundary by which patent administrators and possibly technology developers recognize and delineate contemporary technologies. For example, when a new technology emerges, it may not be classified into a single class in the current classification that exactly matches with its technological characteristics. Also, any new combination of existing technology may well be consisted of multiple technology classes. Therefore, a patent referring to multiple technology subclasses may well impose additional difficulty in understanding the underlying technology and be technologically more complex. We control the number of different technology subclasses assigned to the patent under the U.S. Patent Classification system.[37]

We control the scope of patent by including the number of claims. Each claim may be regarded as an independent patent (Tong and Frame, 1994)[38] and, thus, the number of claims is known to measure the breadth of utility or applicability of the patent.[39] Number of claims are more and more used as a standard control for patent strength in the literature (Lanjouw and Schankerman, 2004).

---

[37] We use the U.S. patent class (USPC) instead of International Patent Class (IPC) for the proxy of technological complexity for the following reasons. In the USPTO, USPC is periodically updated and overwritten for the previous patents. This maintains data integrity between the current patent and the past patents. Moreover, this updated class reflects current, rather than past, views on the cognitive blocks of technology.

[38] In judging patent infringement in the U.S., infringing any single claim in a patent is regarded as infringement on the patent.

[39] In the United States patent law, there are two types of claims: independent and dependent or multiple dependent. While an independent claim stands alone, a dependent claim refers to a claim previously set forth and specifies a particular embodiment or limitation of the invention (35 U.S.C. 112). Because of this distinction, counting dependent claims may not (or in a fractional way) properly reflect the technological scope of inventions. Therefore, we count only the independent claims. We regard any claim that contains a reference to another claim as a dependent claim and subtract them from the total number of claims. We take a natural logarithm of it assuming marginally decreasing nonlinear effects. However, we could not find any notable difference between them and used number of claims in the main estimations.

Age of invention

The mode of use may vary by the length for which an invention has come out and been publicized. The variable “age of invention” measures how many months have elapsed at the time of survey since the invention was filed.

Technology dummies

We distinguish 6 different technology areas using OST/INPI/ISI nomenclature[40] based on International Patent Class.

Description and summary statistics of the variables are presented in Table 8.2.

[40] This is a widely used nomenclature, especially among European researchers, focusing on industry characteristics. This system was developed and updated by three European research institutes: the Observatoire Science et Technology, the INPI (Institute Nationale Proprieté Industrielle), and Fraunhofer Institute for Systems of Innovation Research.

Table 8.2 Sample statistics (restricted sample, in use only, N=651)

Variable	Mean	Std. Dev.	Min	Max	Data source
Internal commercialization	0.737	0.440	0	1	Survey
Explanatory variables					
Inventor in manufacturing unit	0.108	0.311	0	1	Survey
Competence-destroying invention	0.573	0.495	0	1	Survey
Component familiarity (/1000)	0.087	0.151	0.000	2.081	USPTO
Industrial knowledge	0.293	0.196	0	1	Survey
Public knowledge	0.255	0.209	0	0.9	Survey
Collaboration - vertical	0.272	0.445	0	1	Survey
Collaboration - horizontal	0.075	0.263	0	1	Survey
Collaboration - public	0.070	0.256	0	1	Survey
Controls					
Large firm (employees >500)	0.824	0.381	0	1	Survey & Patent
Capital intensity (M$/employee)	0.058	0.088	0	0.823	COMPUSTAT
Dummy for missing capital intensity	0.321	0.467	0	1	COMPUSTAT
Ln(patent stock)	5.014	2.800	0	9.865	PATSTAT
Technological value	2.427	1.087	1	4	Survey
No immediate demand	0.186	0.390	0	1	Survey
% Basic R&D (/100)	0.067	0.153	0	1	Survey
Product invention	0.536	0.499	0	1	Survey
Man-month (normalized)	0.193	0.229	0.005	1	Survey
Number of inventors	2.899	1.983	1	16	Patent
Complexity of technology (# USPC)	4.310	3.305	1	23	Patent
Number of claims	22.823	16.997	1	181	Patent
Age of invention (months)	69.276	12.002	38	92	Patent
Electrical engineering	0.258	0.438	0	1	Patent
Instruments	0.198	0.399	0	1	Patent
Chemistry, pharmaceuticals	0.220	0.414	0	1	Patent
Process eng, special equipment	0.144	0.351	0	1	Patent
Mechanical eng, machinery	0.142	0.349	0	1	Patent
Consumer goods & Construction	0.038	0.192	0	1	Patent

CHAPTER 9. Results

In this section we present the results from a series of regression analyses. We start from simple binary probit regressions with dichotomous dependent variables indicating one type of use (internal or external) regressed on the covariates in the complete-cases (N=1226). Here 0 of the dependent variable indicates all others including nonuse. These results are presented in columns 1 and 2 of Table 9.1.

The remaining models are presented to contrast the differences between internal and external use. Columns 3 and 4 are estimated using binary probit regression in the sample restricted to any commercially used patents (N=651). We use the same dependent variable, internal commercialization path, as in column 1, but 0 indicates only the external commercialization path. Here we removed the nonuse patents and compare internal commercialization directly with external commercialization. The coefficients on variables in these models, thus, will clearly contrast the effects of variables on two polemic uses, internal v. external. Despite the advantage of this model that it can clearly show distinguishing effects between two modes of use, this specification may result in biased estimates of the coefficients if they are subject to two circumstances: 1) when the presence of the third alternative of outcomes (nonuse in this case) affects the choice between two outcomes of our interests (internal and external use in this case) or 2) when factors affecting the censoring procedure (in this case, by nonuse) is not independent

from factors affecting outcomes ("selection effects"). For robustness checks, we estimated the model using two alternative specifications, multinomial logistic regression and the Heckman probit selection model. This will be discussed later in this chapter.

Table 9.1 Results of regression analysis

	Main results: Binary probit				Robustness checks			
	Unrestricted sample		Restricted sample		Multinomial logit (reference=internal)		Heckman probit	
	Internal	External	Internal	Internal: adding interaction term	Nonuse	External	Internal	Selection (any commercial use)
Inventor in manufacturing unit	0.424***	-0.250	0.484**	0.484**	-0.683***	-0.759**	0.469**	
	(0.139)	(0.191)	(0.213)	(0.213)	(0.253)	(0.370)	(0.210)	
Competence-destroying invention	-0.165**	0.166*	-0.273**	-0.272**	0.245*	0.380*	-0.267**	
	(0.079)	(0.100)	(0.119)	(0.119)	(0.137)	(0.206)	(0.117)	
Component familiarity	0.010	0.498**	-0.667*	-0.658*	-0.351	0.706	-0.660*	0.091
	(0.240)	(0.249)	(0.341)	(0.342)	(0.446)	(0.461)	(0.339)	(0.225)
Component familiarity * horizontal collaboration				-0.604				
				(2.618)				
Industrial knowledge	1.145***	-0.197	0.999***	0.998***	-1.986***	-1.385**	0.971***	
	(0.237)	(0.294)	(0.358)	(0.358)	(0.425)	(0.595)	(0.371)	
Public knowledge	-1.303***	0.415	-1.351***	-1.350***	2.185***	1.897***	-1.313***	
	(0.236)	(0.278)	(0.346)	(0.346)	(0.421)	(0.568)	(0.371)	
Collaboration - vertical	0.247**	-0.034	0.223	0.224	-0.414**	-0.301	0.194	
	(0.098)	(0.124)	(0.148)	(0.148)	(0.174)	(0.244)	(0.157)	
Collaboration - horizontal	-0.164	0.532***	-0.601***	-0.559**	-0.082	0.930***	-0.626***	
	(0.161)	(0.177)	(0.201)	(0.265)	(0.300)	(0.334)	(0.197)	
Collaboration - public	-0.005	0.025	0.104	0.102	0.028	0.055	0.070	
	(0.172)	(0.189)	(0.236)	(0.236)	(0.310)	(0.383)	(0.241)	
Controls								
Large firm	0.492***	-0.605***	0.781***	0.780***	-0.475*	-1.295***	0.786***	
	(0.140)	(0.157)	(0.184)	(0.184)	(0.259)	(0.314)	(0.182)	

Table 9.1 (continued)

Ln(patent stock)	-0.055***	-0.020	-0.002	-0.002	0.108***	0.022	0.002	
	(0.017)	(0.022)	(0.027)	(0.027)	(0.031)	(0.045)	(0.026)	
Technological value	0.178***	0.196***	-0.102*	-0.102*	-0.442***	0.151	-0.140	0.250***
	(0.038)	(0.049)	(0.058)	(0.058)	(0.067)	(0.103)	(0.088)	(0.036)
No immediate demand	-0.134	-0.212*	0.108	0.107	0.341**	-0.238	0.158	-0.333***
	(0.093)	(0.123)	(0.151)	(0.151)	(0.163)	(0.251)	(0.176)	(0.089)
% Basic R&D	-0.531**	-0.133	-0.027	-0.031	1.090**	0.419	-0.030	
	(0.250)	(0.313)	(0.405)	(0.405)	(0.451)	(0.689)	(0.394)	
Product invention	0.145*	-0.048	0.091	0.091	-0.246*	-0.193	0.083	
	(0.078)	(0.097)	(0.116)	(0.116)	(0.137)	(0.197)	(0.115)	
Man-month	0.054	0.109	-0.263	-0.265	-0.178	0.103	-0.257	
	(0.179)	(0.218)	(0.266)	(0.266)	(0.319)	(0.421)	(0.263)	
Number of inventors	0.048**	-0.010	0.040	0.040	-0.082**	-0.069	0.034	0.032
	(0.021)	(0.028)	(0.035)	(0.035)	(0.037)	(0.059)	(0.037)	(0.020)
Complexity of technology	-0.010	-0.010	0.014	0.014	0.023	-0.007	0.014	
	(0.011)	(0.013)	(0.018)	(0.018)	(0.019)	(0.027)	(0.018)	
Number of claims	-0.003	0.002	-0.004	-0.004	0.005	0.006	-0.004	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	
Age of invention	0.002	0.006	-0.005	-0.005	-0.007	0.008	-0.006	0.005*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)	(0.005)	(0.003)
Electrical engineering	0.180	0.067	0.024	0.024	-0.369*	-0.071	0.021	
	(0.114)	(0.136)	(0.169)	(0.169)	(0.199)	(0.273)	(0.165)	
Chemistry, pharmaceuticals	0.029	0.000	-0.046	-0.045	-0.055	-0.026	-0.044	
	(0.121)	(0.146)	(0.179)	(0.179)	(0.213)	(0.294)	(0.174)	
Process eng, special equipment	0.018	0.079	-0.139	-0.140	-0.098	0.071	-0.136	
	(0.136)	(0.169)	(0.202)	(0.202)	(0.243)	(0.341)	(0.197)	

Table 9.1 (continued)

Mechanical eng, machinery	0.249*	-0.437**	0.557**	0.555**	-0.316	-0.956**	0.544**	
	(0.134)	(0.193)	(0.224)	(0.224)	(0.230)	(0.391)	(0.225)	
Consumer goods & Construction	0.202	0.003	0.129	0.126	-0.508	-0.105	0.122	
	(0.245)	(0.287)	(0.310)	(0.310)	(0.483)	(0.529)	(0.304)	
Capital intensity (M$/employee)								-1.209***
								(0.400)
Dummy for missing capital intensity								0.217**
								(0.101)
Diversity index of collaboration								0.133***
								(0.050)
Constant	-1.052***	-1.490***	0.770*	0.771*	1.615***	-1.131	1.100	-0.873***
	(0.299)	(0.384)	(0.453)	(0.453)	(0.520)	(0.779)	(0.735)	(0.248)
Heckman's Rho (Arctanh-transformed)							-0.308	
							(0.622)	
Observations (censored)	1226	1226	651	651	1226		1226 (575)	
Log Likelihood	-745.54	-436.97	-318.69	-318.68	-1080.34		-1108.43	
Wald chi2	149.74	103.21	100.98	101.12	247.44		110.13	
Pseudo R2	0.093	0.111	0.145	0.145	0.115		.	

Robust standard errors in parentheses

* denotes 10% significance level, ** denotes 5% significance level, *** denotes 1% significance level.

9.1. Main Results

9.1.1. Main variables

Technology uncertainty

We hypothesized that technology uncertainty will increase the costs of technology transaction in markets and, resultantly, suppress the contracts for technology in markets such as licensing. We operationalized technological uncertainty using the familiarity index of technological components following Fleming (2001).[41] Our interpretation is that the higher the technological familiarity index, the lower the technological uncertainty and, therefore, the higher propensity of external commercialization. Conforming to our hypothesis (M1), component familiarity is significant and positively associated with the probability of external commercialization in the main estimations (column 3 and 4) and Heckman probit (column 7). Note that this effect is significant after controlling for knowledge spillovers from public sources that include patent literature. This indicates that net of knowledge spillovers during the invention process, technological familiarity (and maturity of technology) still has some impact on the commercialization process. However, the significance disappears in the multinomial logit model. Therefore, we find only weak evidence about the association between the external path of commercialization and technological uncertainty. One source of the weak association is because our public knowledge variable mediates technology familiarity. When we ran the same regression without the public knowledge variable, the coefficient on component familiarity turned

[41] Fleming (2001) found that this measure is in inverted-U relationship with the utility of the invention. In our estimation, curvilinear relationship was not confirmed.

significant. Another source of the weak association may be attributed to the characteristic of this measure. While Fleming interpreted component familiarity as a measure of potential technological variation or maturity, this may also represent the size of the technology supply or technological interdependency. As the size of a pool of similar technology with the focal invention increases, the alternative buying options for the potential buyer of the technology will increase. The former, technology supply effects, therefore, would reduce the demands for the technology in the market for technology. Also, as the volume of the components of similar technological nature increases, they may link to each other in a more complex way or, in other words, technological interdependency may increase. This will put additional complexity in assessing the prospect and value of the focal technology and therefore increase transaction costs. These confounding effects or measurement noises inevitably accompanying the patent indicators will limit the effectiveness of this measure in capturing technological uncertainty.

Complementary assets

The patents having a strong internal position of complementary assets are hypothesized to be more likely to take an internal commercialization path. We operationalized strong internal complementary assets using two measures: 1) whether an inventor belonged to a manufacturing unit at the time of invention and 2) whether an invention is linked to existing competences (i.e., competence-enhancing rather than destroying) (Anderson and Tushman, 1990).

In column 1, the coefficients on “Inventor in manufacturing unit” is highly significant and positive, indicating that a patent from manufacturing units is more likely than a patent from non-manufacturing units (e.g., dedicated R&D units) to internally commercialize. The effects of complementary assets on the choice of commercialization path are clearly shown in the bimodal comparisons (column 3 through 7). Strong position of internal complementary assets is likely to increase the probability of internal commercialization compared to either nonuse or external commercialization.

An alternative measure of complementary assets also has an expected sign. When an invention is not targeted to improving a current product or process (“competence-destroying invention”), it is more likely to be used externally. When the dependent variable is “internal commercialization,” the estimated coefficients on this variable are significant (at 5% level) and negative across all models, while positive for “external commercialization.” In the full model of the restricted sample, for a patent from a large firm in electrical engineering, being an inventor belonging to a manufacturing unit raises the probability of internal commercialization by 17.8 percentage points, holding other variables constant at their means or modes. In the same conditions, the competence-destroying invention lowers the probability of internal commercialization by 5.1 percentage points.

In conclusion, we are confident that a strong position of internal complementary assets will increase the probability of internal commercialization and lowers the probability of external commercialization.

External knowledge

We examine the effects of external knowledge on the organizational trajectory of commercialization using the variables "industrial knowledge" and "public knowledge" by distinguishing the sources of external knowledge. The diverging effects of these variables on the commercialization path are as predicted. Industrial knowledge has a highly significant and positive impact on the probability of internal commercialization supporting hypothesis M4a. On the other hand, public knowledge has a highly significant and positive impact on the probability of external commercialization supporting hypothesis M4b. Interestingly, public knowledge has a significant and negative impact on the probability of internal knowledge. Although we controlled for firm size, one can argue that large firms would not utilize external knowledge as much as small firms would. In order to test the robustness of the impact of external knowledge over firm size, we ran the same regressions with the firm size variable excluded in two split samples: large firm only and small firms only. Signs and significance on both external industrial knowledge and external public knowledge were still maintained in both of the split estimations, indicating that the results from the main estimation are indeed robust against firm size. However, the magnitudes of the coefficients are larger in the small firm estimation for both variables. This suggests that the impact of external knowledge on choice of organizational paths of commercialization might depend on firm capabilities[42].

Collaboration effects

[42] In the sample, small firms utilize more external public knowledge than large firms when their inventions are commercialized, regardless of modes (N=651, small firm mean=0.287, large firm mean=0.246, $Pr(|T| > |t|) = 0.0605$). However, the differences become insignificant in each mode of commercialization.

Collaboration raises the probability of internal and external commercialization when the importance of external knowledge is not controlled.[43] After controlling for external knowledge, the coefficient on collaboration remains significant (and positive) for external collaboration but not for internal collaboration. (Not reported. Available on request.) This finding indirectly indicates that, while internal commercialization exploits a knowledge advantage from collaboration, external commercialization exploits *both* knowledge advantage and network advantage from collaboration. We clarified these suspects by distinguishing the types of collaboration by relationship with collaboration partners. In hypothesis M3a, we argue that collaboration with vertical firms will bring forth knowledge and learning advantage, which is suitable for integrating into the downstream commercialization process. This seems to be supported at the first look from the full model estimation as indicated by a highly significant and positive coefficient on "Collaboration -vertical" in the full sample (column 1). However, the effects of vertical collaboration on organizational paths of commercialization are not confirmed as indicated by insignificant estimates of the coefficients in the bimodal estimations (columns 3 to 7). The vertical collaboration has discriminating effects on internal commercialization only against nonuse as indicated by significant and negative estimation of the coefficient in the multinomial logistic regression (column 5). In conclusion, hypothesis M3a is only partially supported.

[43] We test two different measures of collaboration: 1) binary variable constructed from survey and patent documents (coded 1 for collaboration and 0 otherwise) and 2) binary variable constructed only from survey (coded 1 for collaboration and 0 otherwise). We had robust results for both measures. Although not reported, this may be estimated by comparing coefficients on the collaboration variables in models 2 and 4.

On the other hand, collaboration with firms in a horizontal relationship uniquely affects external commercialization. Having collaborated with horizontal firms raises the probability of external commercialization by 12.5 percentage points, holding others at their means or modes (column 2). Horizontal collaboration especially raises the probability of an external path against an internal path as indicated by a negative sign on the coefficient of horizontal collaboration in the restricted sample.

To test hypothesis M3c, we added the interaction term (component familiarity * horizontal collaboration) in column 4. The coefficient on the interaction term is not significant in the model, but this does not tell us that there is no interaction effect. In a nonlinear model, interaction terms (sign, magnitude, and significance) vary with covariates (Ai and Norton, 2003). So we plotted z-statistic of the interaction term against the predicted probability using "inteff" function in STATA (Norton, Wang, and Ai, 2004). As Figure 9.1 shows, most significant interaction effects ($|z|>1.96$ at conventional significance level, $P<0.05$) have negative signs and are located on the right side of the graph where the internal commercialization is predicted (predicted probability>0.5). Also, regardless of significance, interaction terms show decreasing trends as the probability of internal commercialization increases. Recall that both component familiarity and horizontal collaboration have a negative impact on the internal collaboration in our estimations. The negative interaction effect, thus, indicates that the effects of horizontal collaboration are stronger for technologically more uncertain inventions (or a higher likelihood of internal commercialization). This result supports hypothesis M3c. However, the magnitudes of interaction effects are very small (around 0.3 percentage points).

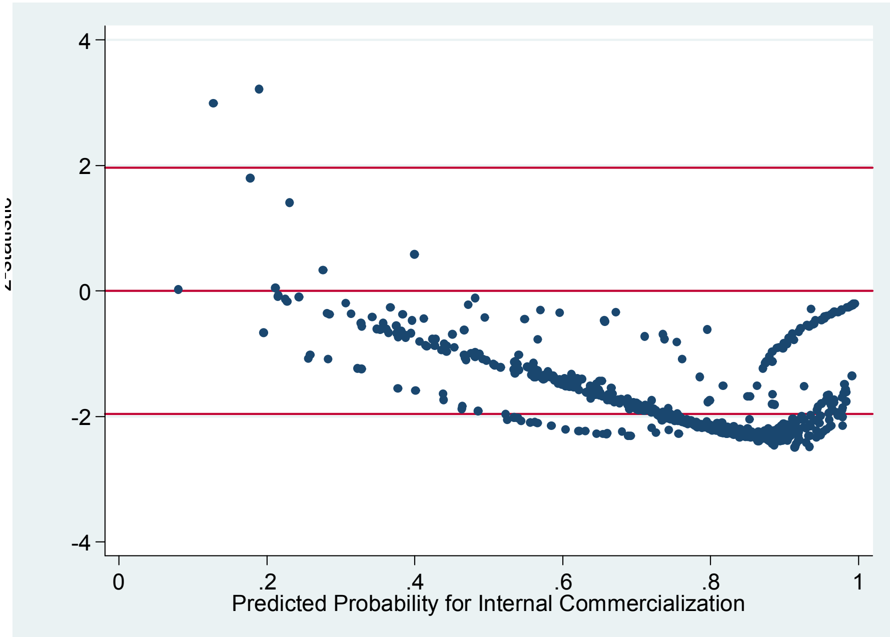

Figure 9.1 Interaction effects of component familiarity and horizontal collaboration

9.1.2. Other variables

Technological value

In the full sample including nonuse, technological value is significant and positively associated with both types of commercialization paths. Interestingly, the coefficients on this variable are larger for external use than for internal use (columns 1 and 2). In the restricted sample and multinomial logistic estimates, it is clearly shown that the higher technological value, the higher propensity to externally commercialize, holding all others constant. One possible explanation is that, to find a commercial application, technologically advanced inventions may require broader and more diverse technological capability that a single firm can hardly command. Another explanation is that

technologically advanced inventions are less uncertain in value and promote market transactions. However, given that we controlled general technological uncertainty, internal demands, and whether or not the invention is competence-destroying, these explanations are not fully satisfying. Another explanation might be found in inherent endogeneity involving in the assessment of the "value." Due to technological complexity and cognitive limitation, it may be very hard for an inventor to assess technological values of certain technologies on an absolute measure. Because of this ambiguity in evaluating technological value, inventors may assess technological superiority of their inventions by watching the reaction of the community. So external commercialization is associated with high technology value partly because the interests from others accompanying the external commercialization may have affected inventors to "inflate" the technology value.[44] This is one possible avenue for future research.

Firm size

Our estimates show strong and consistent results that patents from large firms are more likely to take an internal commercialization path than an external path. The coefficients on "large firm" are highly significant and have expected signs (positive on internal use and negative on external uses). This result is consistent with findings by Gambardella et al. for European firms (Gambardella, Giuri, and Luzzi, 2007). The firm size effects are substantial after controlling for complementary asset effects. Gambardella, Giuri and Luzzi discuss two reasons driving the lower propensity of large firms' licensing. First, large firms are better positioned to integrate complementary assets than small firms. Second, given that large firms generally have stronger market presence, "rent dissipation

[44] Personal communications with Diana M Hicks.

effects" from licensing will be greater for large firms than small firms where the revenue earned from licensing is invariant of firm size (Arora and Fosfuri, 2003; Arora, Fosfuri, and Gambardella, 2002). Our finding of strong firm size effects even after controlling for the internal strength of complementary assets corroborates the validity of the rent dissipation explanation.

Unlike a finding from Kim and Vonortas (2006) for licensing propensity, our estimation does not show a significant relationship between the patent stock of a firm and the propensity to commercialize externally (which includes licensing).

Strength of patents

Our measures of patent strength (number of claims and number of technology classes) do not have a significant impact on commercialization paths. This is different from what Gambardella et al. (2007) found from the PatVal-EU survey. This is probably because of multiple meanings attached to the measures. As Gambardella et al. claimed, as technological scope and complexity increases, the possibility of inventing-around will decrease and, thus, the protective role of the patent will be strengthened. This is one interpretation. Another interpretation is that the larger scope and higher complexity will increase transaction costs. These multiple connotations from the same measure actually work in the opposite directions with regard to the organizational paths of commercialization. To overcome this difficulty of measurement, we estimated the model with additional control of industry level strength of patent appropriability constructed

from the Carnegie Mellon survey (Cohen, Nelson, and Walsh, 2000).[45] The estimates of our independent variables are robust against additional control of this variable. However, this appropriability measure is also insignificant.

9.2. Robustness Checks

We created a nominal variable "mode of use" by coding 0 for nonuse, 1 for internal use, and 2 for external use.[46] Then we ran a multinomial logit with "internal use" as a comparison group.[47] The results are shown in columns 5 (nonuse) and 6 (external use) of Table 9.1. Multinomial logit assumes the Independence of Irrelevant Alternatives (IIA) which means that the odds should not be affected by addition or omission of another outcome category. Small-Hsiao tests of IIA assumption indicate that we cannot reject the null hypothesis that omission of nonuse is irrelevant to the choice between internal and external use at 5% significance level.[48] Multinomial logit model is proper based on empirical tests. In the textbook, multinomial logit model is said to be proper when the outcomes are distinct and not substitutes for one another (Long and Freese, 2006). In our model, the modes of uses are distinct (as shown by the results of Wald and Likelihood Ratio tests for combining alternatives). However, they may be substitutes for one another.

[45] We used the mean of patent effectiveness at industry level (transformed into NAICS from International SIC).
[46] We did not distinguish "licensed" from "for a new firm" because of the small number of observations assigned to each of these two categories.
[47] Multinomial logit should not be much different from multinomial probit except in extreme values. We ran multinomial logit because multinomial probit is known to be not as reliable as multinomial logit (Long and Freese, 2006).
[48] Small-Hsiao test results are different in each run because it uses different random seeds (Long and Freese, 2006). However, 9 out of 10 tests we have run show that we cannot reject the IIA assumption for nonuse.

The probability of mode choice when every patent is forced to use will be different from when nonuse is allowed. For example, if a bargaining failure view of strategic nonuse (Merges, 1994) is valid, then adding or removing a choice for strategic nonuse will affect more on licensing than other choices. This point is explicitly dealt with in Part III. Another complexity of interpretation stems from the way we classify the modes of use. We assign those patents in dual use (both internal and external use) to external use. Theoretically, those dual-use patents should have characteristics of both internal and external use and possibly make our interpretation more complex. However, at least empirically, it seems that the characteristics of dual-use patents are more bound with the characteristics of external use. We test the distinctiveness of dual use from purely external use using multinomial logit regression and cannot reject the null hypothesis that they are the same in relations with our covariates (Chi2(23)=26.19, P>chi2=0.292). Also, according to some studies, in the situation where IIA is violated, a well-specified multinomial logistic model is comparable in sign and significance of coefficients with nested or mixed logistic models (Cushing and Cushing, 2007; Train, 2003). Indeed, our main estimation, binary probit regression in the restricted sample, does not show a notable discrepancy from the multinomial logistic regression. Therefore, we conclude that, despite some theoretical concerns, taking the binary probit specifications in the restricted sample as the main results is acceptable.

Our final specification, the Heckman selection model with selection of "any use" in the first stage, addresses the selection bias problem. In the selection equation, we regressed "any commercial use" on six variables: technology value of patents, collaboration, non-

commercial purpose of R&D, number of inventors, age of invention, and component familiarity. The selection probability term fed into the main equation (Heckman's rho) is, however, not significant. This indicates that, at least, we do not have significant bias in analyzing modes of use due to the propensity of any commercial use. The empirical validity of both the Heckman selection and multinomial logistic regression specifications, in turn, indicates that simple binary probit regressions in the commercialization sample would also be valid, and the estimates from all three specifications would be consistent to each other. Indeed, the estimates from all the models are quite consistent. For simplicity's sake, we use binary probit regressions as our main models.

Before we conclude this section, let us briefly address another possible source of bias – possible self-selection effects related to the missing values on some of the covariates. Because the number of dropped observations is substantial, we examined the possibility that the listwise deletion has to do with self-selection by running the Heckman probit selection model with a dummy for complete cases as the dependent variable in the selection equation. The self-selection effect is not significant as indicated by insignificant correlations (Heckman's rho) between error terms in the selection equation and error terms in the outcome equation. Also, we ran the same models with missing values on "technological value" replaced with its mean (=2.19) and dummy for missing added.[49] While we have about 16% larger sample size for binary probit models (from N=1226 to 1415) through this way of missing value handling, we found no notable differences

[49] We also tested different imputation methods. For example, we imputed predicted value estimated from regression equation with "technological value" regressed on a set of value-predicting patent indicators. Almost all predicted values, however, narrowly distributed around the sample mean and did not make much difference from using simply mean.

between dummy-adjusted models and the original ones. We also ran the models in the imputed sample using bootstrap re-sampling methods. A basic idea is that, if there is a significant bias due to missing values, then the coefficients and standard errors estimated for the subsample will be different from the original one. We re-sampled 50 random subsamples from the imputed sample (N=1415) and calculated bootstrap coefficients and standard errors. The results are quite similar to the main results. Furthermore, we found no significant difference in the means of our dependent variables between the full set (N=1807) and the uncensored subset (N=1226). The only significant difference of means of independent variables between two groups is found for collaboration diversity. However, even if listwise deletions are not totally random to some extent, this does not indicate that we will have biased estimates for the following reasons: First, our sample is not censored by the characteristics of the dependent variables (Wooldridge, 2002). Second, the signs and significance of the coefficients in binary probit models are almost identical with them in probit selection model (not reported). This tells us that a bias that may stem from omitting the selection correction term is ignorable. Therefore, using binary probit analysis for the complete cases is appropriate.

9.3. Breakdown of External Commercialization

External commercialization paths in our estimation indeed enclose several different uses of patents: licensing, cross-licensing, and using patents for starting a new firm. To further examine diverging effects of our key independent variables on different paths of external

commercialization, we estimated two additional models. First, to examine the difference between licensing and "new firm," we estimated a multinomial logistic model with four outcome levels: nonuse, internal commercialization, licensing (including cross-licensing), and use for a new firm. We use internal commercialization as the reference category. Second, to clarify diverging effects between cross-licensing and unilateral licensing, we estimated probit selection model with all kinds of licensing as a selection variable and cross-licensing as the dependent variable in the main equation. Because of the small number of observations for cross-licensing (N=40), we estimated the main equation only with several significant variables. As indicated by strongly significant Heckman's rho, independent estimation of cross-licensing propensity without conditioned on the licensing propensity may be biased. The results are presented in Table 9.2. Both models passed key specification tests and show acceptable goodness-of-fit statistics ($p<0.0001$ for multinomial logistic regressions and $p<0.0005$ for Heckman probit).[50]

The estimates for licensing propensity are largely similar with the main results. The signs of main independent variables are maintained. However, competence-destroying invention and component familiarity are not significantly associated with licensing. A competence-destroying invention is likely to be commercialized externally but particularly via establishment of a new firm rather than licensing. This observation supports Schumpeter's notion of "creative destruction" and is consistent with Anderson and Tushman's (1986) observation on the tendency of small and new firms to conduct competence-destroying innovation. One possible reason for no significant impact of

[50] Some runs of Small-Hsiao tests indicate that IIA assumption does not always hold for the multinomial logistic regressions. However, as we discussed in the previous section, this does not indicate that the estimation is significantly biased in the signs and significance of regression coefficients.

competence-destroying invention on the propensity to license is because it may have a negative impact on cross-licensing. Patents offered for cross-licensing agreement are generally used to obtain access to others' technologies in complex industries (Grindley and Teece, 1997; Hall and Ziedonis, 2001). They may not involve as much know-how transfer as in unilateral licensing and tend to occur between symmetric firms (Nagaoka and Kwon, 2006). Therefore, patents offered for cross-licensing may be related to the existing competences shared by similar firms. Indeed, the Heckman selection estimation shows a negative sign on competence-destroying invention, although not significant. Another reason is related to a measurement error. In the question asking whether the invention project targets a new or improved product or process, the survey did not explicitly state whether it is with regard to the firm or to the industry. If the respondent answered the question with regard to the industry, then the competence-destroying invention has no advantage for licensing or cross-licensing as well as for internal commercialization.

Component familiarity is not significantly associated, albeit marginally so (z-statistic=1.49), with new firm formation (column 3). However, the coefficient is positive. This is inconsistent with what Shane (2001) found for the propensity to license university patents to start-ups. He argued that start-ups based on university patents should be more likely to form in the nascent technologies because of no disadvantage of start-ups (relative to the incumbents) in market power, learning curve, scale economy of production, and complementary assets in new technologies. However, consider the following counter arguments. In mature technology, demands for the technology are

well-established, and there will be larger small opportunities, which can be covered by niche players. Large incumbents having a profit model from a large production facility will not properly cope with these niche areas. Also, in mature technology, innovation labor will be more widely distributed and, therefore, procuring complementary assets required for commercialization from the markets will be easier. These counter arguments refute Shane's claims that immature technology is more attractive to start-ups. However, more importantly, there may be some fundamentally different mechanisms working between science-based start-ups and corporate spin-offs. In addition, as we argued in Hypothesis M1, lower transaction costs (both in the market for technology and in the financial market) in mature technology favor corporate spin-offs. Deeper analysis on this aspect will be an interesting topic for future research.

Turning to the licensing propensity, component familiarity shows insignificant association with the licensing propensity (columns 2 and 5). Actually, the effects of component familiarity on external commercialization are concentrated on cross-licensing as indicated by a significant and positive coefficient in the Heckman probit estimation (column 4). Increase of technological familiarity is likely to increase the propensity of cross-licensing relative to the propensity of unilateral licensing. Component familiarity has indirect effects on the licensing propensity via public knowledge and collaboration with public organizations. When we estimated the model without these two variables, the significance of the coefficient on component familiarity was enhanced (but still marginally insignificant). In another estimation limited to the sample composed of commercial use, the coefficient on component familiarity is significantly and positively

associated with the licensing propensity. On the other hand, exploitation of public knowledge and collaboration with public organizations during the invention process may have some spurious effects related to technological uncertainty. Provided that knowledge exchange is reciprocal, collaboration during the invention process may have generated some outward spillovers. This effect will be greater for collaboration with public organization given that they are more dominated by open science norms. Also, knowledge in the public domain is generally available for anybody. Therefore, invention that had incorporated more public knowledge may be better understood by others and be less uncertain in technology prospect.

One interesting finding is that public knowledge has particularly strong positive impacts on formation of patent-based spin-off. Note that we excluded from the sample independent start-ups and spin-offs/start-ups from academic or public organizations. In the literature, it is known that public knowledge plays an important role for academic or independent start-ups (Zucker and Darby, 1996; Zucker, Darby, and Armstrong, 2002). Our finding indicates that public knowledge will also be important for corporate spin-offs. On the other hand, whereas patents offered for unilateral licensing are likely to have utilized more public knowledge (as predicted in Hypothesis M4b), patents offered for cross-licensing are less likely to have utilized public knowledge than unilateral licensing. This discrepancy indicates that open innovation and institutional approach, besides transaction costs, are indeed importants factor affecting the innovation.

As we argued in Hypothesis M3b, horizontal collaboration has indeed particularly strong impact on cross-licensing (relative to unilateral licensing as well as an internal path of commercialization). Finally, we added a new variable, "complexity of product technology," in the cross-licensing estimation. This measure is constructed from the survey question asking how many patents are combined to produce a target product. Consistent with the previous observation (Cohen, Nelson, and Walsh, 2000; Hall and Ziedonis, 2001), our estimate shows cross-licensing is more likely to occur in complex products relative to unilateral licensing.

Table 9.2 Results of regressions for further examination of external commercialization paths

	Multinomial logit (reference=internal)			Heckman probit	
	Nonuse	Licensing	New firm	cross-licensing	Selection (licensing)
Inventor in manufacturing unit	-0.694***	-1.701***	0.510		-0.542*
	(0.254)	(0.628)	(0.473)		(0.289)
Competence-destroying invention	0.245*	0.309	0.655*	-0.157	0.103
	(0.137)	(0.231)	(0.386)	(0.211)	(0.108)
Component familiarity (/1000)	-0.372	0.528	0.991	1.203**	0.279
	(0.440)	(0.491)	(0.666)	(0.475)	(0.255)
Complexity of product technology				0.010*	
				(0.005)	
Industrial knowledge	-1.994***	-1.531**	-1.050		-0.349
	(0.425)	(0.667)	(0.963)		(0.301)
Public knowledge	2.167***	1.423**	3.421***	-1.192**	0.077
	(0.421)	(0.675)	(0.760)	(0.595)	(0.307)
Collaboration - vertical	-0.415**	-0.421	0.103		-0.120
	(0.174)	(0.278)	(0.408)		(0.125)
Collaboration - horizontal	-0.074	1.105***	-0.093	1.284***	0.613***
	(0.299)	(0.351)	(0.639)	(0.301)	(0.182)
Collaboration - public	0.035	0.335	-1.027		0.206
	(0.309)	(0.414)	(0.672)		(0.190)
Large firm (employees >500)	-0.465*	-1.145***	-1.581***		-0.414**
	(0.258)	(0.381)	(0.442)		(0.174)
Ln(patent stock)	0.108***	0.047	-0.058		-0.009
	(0.031)	(0.053)	(0.073)		(0.024)
Technological value	-0.442***	0.111	0.260		0.153***
	(0.067)	(0.116)	(0.180)		(0.051)
No immediate demand	0.339**	-0.278	-0.072		-0.207
	(0.163)	(0.285)	(0.403)		(0.130)
% Basic R&D (/100)	1.105**	0.748	-1.041		0.241
	(0.452)	(0.742)	(1.156)		(0.305)
Product invention	-0.250*	-0.383*	0.288		-0.176*
	(0.137)	(0.218)	(0.341)		(0.097)
Man-month (normalized)	-0.167	0.364	-0.864	0.703	0.273
	(0.319)	(0.464)	(0.742)	(0.447)	(0.229)
Number of inventors	-0.083**	-0.110	0.035		-0.032
	(0.037)	(0.068)	(0.094)		(0.029)
Complexity of technology (# USPC)	0.023	-0.034	0.049		-0.023
	(0.019)	(0.035)	(0.035)		(0.016)
Number of claims	0.005	0.001	0.016**		0.000
	(0.005)	(0.006)	(0.008)		(0.003)

Table 9.2 (continued)

Age of invention (months)	-0.006	0.012	-0.005		0.006
	(0.005)	(0.010)	(0.015)		(0.004)
Electrical engineering	-0.363*	0.143	-0.687		0.146
	(0.199)	(0.315)	(0.448)		(0.145)
Chemistry, pharmaceuticals	-0.058	0.084	-0.255		0.037
	(0.213)	(0.345)	(0.461)		(0.159)
Process eng, special equipment	-0.100	0.186	-0.107		0.063
	(0.243)	(0.386)	(0.531)		(0.181)
Mechanical eng, machinery	-0.311	-0.551	-2.406**		-0.196
	(0.230)	(0.431)	(1.070)		(0.197)
Consumer goods & Construction	-0.503	0.190	-0.643		-0.012
	(0.484)	(0.616)	(0.910)		(0.298)
Constant	1.617***	-1.403	-2.727**	-2.089***	-1.501***
	(0.520)	(0.906)	(1.240)	(0.313)	(0.420)
Heckman's Rho (Arctanh-transformed)				1.120***	
				(0.426)	
N (censored N)		1226		1226 (1104)	
Log Likelihood		-1154.73		-417.01	
Wald chi2		309.24		27.41	
Pseudo R2		0.125		.	

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

CHAPTER 10. Conclusion to Part II

This study examined the impacts of technological uncertainty, strong internal complementary assets position, characteristics of knowledge search, and collaboration on the organizational path of commercialization. Departing from Teece's framework on the profitability of innovation, we synthesized various theories to explain why firms choose different organizational paths in the downstream commercialization process. We found that technological uncertainty suppresses external paths of commercialization. The main argument of this hypothesis builds on TCE but also incorporates the evolutionary explanation of technological development. Stage of technological development, technological uncertainty, and profitability of innovation are interrelated with each other.

As Teece argued and many following studies showed, strong internal position for the complementary assets have a strong positive impact on the internal commercialization paths. Also, as Tushman and Anderson argued, we found that there was a strong organizational inertia for a firm to tend to keep doing what it had been doing. This implies that firms' innovation activities would have a strong path dependency and, therefore, may well fall into the competence trap (Levinthal and March, 1993; Levitt and March, 1988). This finding contributes to the Teecian framework of profitability of innovation and arguments of markets for technology by providing a direct test of the effects of co-specialized complementary assets on a choice of commercialization paths.

Also, in explaining the relationship between strong coupling with internal complementary assets and vertical integration of downstream commercialization processes, we enriched the discourse by synthesizing theoretical implications from TCE and KBV of a firm. One avenue of future research will be looking at how the effects of co-specialized assets on commercialization paths are moderated by the characteristics of technology (e.g., general purpose v. specialized) or by the stage of the technology development cycle. Our conjecture is that the impact of co-specialized assets on the choice of commercialization paths will be weaker for general-purpose invention or in mature technology.

Further departing from Teece, we argue that openness of innovation processes and network relationship should affect the choice of commercialization path. Consistent with our hypothesis, empirical results show that external knowledge from industrial nature increases the propensity of internal commercialization. Industrial knowledge tends to focus more on specific industrial problems and require for more hands-on knowledge typically acquired from field experience. These characteristics of industrial knowledge would make coherent authoritative controls more efficient than distributed controls across firm boundaries. As hinted by KBV, internal synergy of this type of technology is expected to be higher. Detailed examination of external paths of commercialization revealed some interesting aspects of public knowledge. External public knowledge has a positive impact on licensing, particularly strong impact on formation of patent-based corporate spin-offs, and either weaker or even negative impact on cross-licensing. Furthermore, proceeding one step further from the open innovation arguments, it shows that the nature of external knowledge should be taken into consideration in studying

innovation. The previous empirical studies focused on how broadly or deeply firms sourced external knowledge and how they affected intermediate output of innovation process or firm performance (Katila and Ahuja, 2002; Laursen and Salter, 2006). In doing so, they did not turn their attentions to the qualitative differences of sourced knowledge. Other studies examined a limited number of leading firms to show how they had successfully utilized some types of external knowledge for innovation (Dyer and Nobeoka, 2000; von Hippel, 1988). This study attempts to overcome the weaknesses of both studies by examining the impact of different types of external knowledge in a large-scale, cross-industry sample. Furthermore, it reveals that not only the different nature of external knowledge has a different impact on innovation but also it would be bound with a different commercialization strategy. While external industrial knowledge is conducive to internal commercialization, external public knowledge spawns external commercialization. Or, the other way around, firms that chose an internal integration strategy would have sought more industrial knowledge, while firms that chose to provide their inventions to external parties for commercialization might have relied more on public knowledge. Certainly, the analysis leaves more questions to be answered. Although we tried to justify distinctiveness between external industrial and public knowledge in the context of mode of commercialization both theoretically and empirically, it still leaves ambiguity in concepts and measurement. First, it overlaps with a basic-applied distinction. We argued that they were different because external public sources can deliver an applied type of knowledge, and external industrial sources can deliver a basic type of knowledge. We also controlled for the basicness of an R&D project. We suggested—separate from a basic-applied nature—technological fitness,

learning-curve effects, and inclusion of organizational routines as some discriminating characteristics of this distinction. However, they need to be better articulated in the practical context. Second, external public knowledge is confounded with the maturity of the field of technology, as we discussed in Part II. This also contributes to the ambiguity. In summary, further research on the characteristics, drivers, and impact of the different types of knowledge is required.

Collaboration has diverging effects on the choice of commercialization paths, depending on the characteristics of collaborating partners. While collaboration with firms in a vertical relationship tends to favor internal paths, collaboration with firms in a horizontal relationship tends to favor external paths. In particular, horizontal collaboration is strongly associated with licensing (both unilateral and cross-licensing). This finding shows that collaborative networks, net of knowledge flows, influence the organizational trajectory of commercialization. Furthermore, it shows that relative position of the innovator in the network is indeed an important predictor of the trajectory. By the relative position in the network, we do not mean the structural or topological relations that many studies of networks focus on (Owen-Smith and Powell, 2004), but the relative positions in a value chain or in competitive relations in the product markets. Previous studies argued why particular ties affect the firm or innovation performance (Afuah, 2000; Dyer and Nobeoka, 2000; Gulati and Higgins, 2003; Uzzi, 1996). This study contributes to the field by arguing and showing that firms utilize different types of networks for different innovation strategies. As a novel contribution, it shows that perspectives on collaborative networks have unique explanatory powers in the region that TCE cannot address. Where

technological uncertainty is high, collaboration has a stronger impact on the choice of the organizational path of the downstream process of innovation. This finding empirically corroborates Granovetter and Powell's (Granovetter, 1985; Powell, 1990) arguments that economic theories alone are incomplete in explaining social behavior so that network perspectives can complement them.

PART III. STRATEGIC NONUSE OF PATENTS

CHAPTER 11. Introduction to Part III

Betraying the original design goals of the patent systems, some patents add friction to innovation systems. For example, some patents heighten an entry barrier into a product market, undermine a rival's competitiveness, or increase the transaction costs of technology. As technology has become more critical in the competitiveness of contemporary firms (Baumol, 2002; Jaffe, 2000) and the filings of patents have exploded (Kortum and Lerner, 1999; Shapiro, 2000; van Zeebroeck et al., 2008), firms have been more attracted to using patents for these purposes (Blind et al., 2006; Cohen, Nelson, and Walsh, 2000; Shapiro, 2000). Using patents to enhance strategic advantage in the competitive landscape is not a recent phenomenon at all.[51] However, a wider diffusion and heightening stack of them during recent years has raised fundamental concerns about whether the current patent system is working as it was designed (Shapiro, 2000). Especially pertinent to these woes are patents that generate economic value by preventing others from using the patented technology while being neither integrated into a commercial application nor licensed to others. We call this class of patents "strategic nonuse patents." Strategic nonuse patents are distinct from commercially exploited patents in that they are not used for commercial products or processes. They are also

[51] A classic example is the "Fleming valve" patent issued in 1905, which stalemated development of radio communication technology (Marconi Wireless & Tel. Co. v. De Forest Radio Tel & Tel. Co., 236 F. 942 (S.D.N.Y. 1916)). Other historical cases are nicely described in the following legal literature: (Merges, 1994; Saunders, 2002; Turner, 1998).

distinct from plain nonuse patents (or sleeping patents)[52] in that they generate strategic benefits. While this class of patents benefits an individual firm that owns them with a strategic advantage in the competitive landscape, it may undermine competitiveness of an economy as a whole and the potential for scientific and technological progress (Heller and Eisenberg, 1998; Saunders, 2002).

Strategic nonuse patents may have significant negative effects on resource allocation and on the innovative capabilities of a society. A patent system was put in place to "promote the progress of science and useful arts" (U.S. Constitution, art. I, sec. 8), basically by two mechanisms: first, incentivizing investment in R&D and, second, enforcing disclosure of the resultant technical arts to the public. A core instrument that enables these mechanisms is the property rights awarded to inventions and temporary exclusivity legally allowed over using, making, and selling the inventions. Using these legal instruments, the inventors would be able to exclude others from the product market based on the patented technology and, resultantly, appropriate their investment on R&D and the follow-up commercialization. On the other hand, because of the monopoly, society may suffer, at least temporarily, from a suboptimal level of the supply of goods and inefficient allocation of resources, both in R&D and in production. A society is willing to tolerate the potential loss of social efficiency inevitably accompanying the temporary monopoly only because it expects a larger amount of rewards (beyond just countervailing the loss) in the following forms: increased level of investment in R&D, introduction of innovative products, and spillover of useful knowledge. Strategic nonuse patents are often criticized

[52] This class of nonuse patents is conceptually equivalent to a "sleeping patent" (Gilbert and Newbery, 1982) or "paper patent."

as causing excessive duplicate investment in R&D, blocking introduction of an innovative product, slowing down innovation, and incurring unnecessary costs for managing patents and, therefore, seem to violate the "good-will" bolstering the patent system (Merges, 1994; Turner, 1998). However, they are lawful (Merges, 1994; Turner, 1998) and increasingly exploited by contemporary firms (Sheehan, Martinez, and Guellec, 2003).[53] Studying strategic nonuse patents will be of crucial importance for understanding innovation as well as patent system reform.

A number of legal studies have investigated historic cases of strategic nonuse patents. Also, some economic studies have theoretically discussed social welfare aspects, anti-competitiveness effects, and the effects of the presence of strategic nonuse patents on the patent system. However, there are only a limited number of empirical studies, most of which, except Blind et al, are at the industry or firm level (Blind et al., 2006; Ceccagnoli, 2009; Cohen, Nelson, and Walsh, 2000; Reitzig, 2004; Ziedonis, 2004). Using information from the U.S. inventors survey, this study reveals an empirical reality of the motives for patenting and reasons for patent nonuse at the patent level. Then it tests the discriminating effects of firm and technology characteristics on the propensity of strategic nonuse patents. In particular, this study tests how the size of upstream and downstream assets of a firm affects the propensity of patents being used for strategic

[53] According to some surveys (Giuri et al., 2007; Sanders, Rossman, and Harris, 1958), about 30% to 40% of the issued patents are reportedly not used. Sanders et al. (1958) report 42% of the surveyed U.S. patents are not used. After surveying European inventors, Giuri et al. (2007) report that about 36% of European patents are not used. One survey reports that about a half of nonuse patents are strategic nonuse patents (Giuri et al., 2007). Regardless of a patent's being actually used or not, strategic motives of patenting have grown significantly recently (Blind et al., 2006; Cohen et al., 2002; Harabi, 1995; Sheehan, Martinez, and Guellec, 2003).

defensive purposes. It also tests the effects of technological uncertainty and maturity on the strategic nonuse.

CHAPTER 12. Analytic Framework

Patent nonuses can be broken down into two classes: strategic nonuse and other nonuse. Some patented inventions that are not integrated into products or sold in the market for technology may generate strategic rents. In discrete industry, where products are built on a relatively small number of technologies, development of substitutable technology by competitors will be a big threat to the owner of the original technology. For example, in the pharmaceutical or polymer industries, profits from a particular chemical material of a certain effect will not accrue to the original inventor if he fails to prevent alternative methods of synthesis that lead to a material of the same effect. In this industry, the original inventor often files for "fence" patents to prevent competitors from inventing-around the technologies (Cohen, Nelson, and Walsh, 2000). In complex industries, where a large number of technologies is integrated into a final product, such as electronics or semiconductors, patents are often filed to block competitors from further developing the downstream complementary technologies (Cohen, Nelson, and Walsh, 2000). Some patents, especially those filed by semiconductor firms, are included in a broader patent portfolio to ensure freedom-to-operate (Grindley and Teece, 1997) and, sometimes, used as a bargaining chip to enhance the position of negotiation in cross-licensing deals (Hall and Ziedonis, 2001). Either fence or blocking would not generate financial benefits directly from the patented technology but generate strategic benefits in the form of stronger protection of core technologies or raising competitors' innovation costs. Some

blocking patents are used strategically for improving position in negotiation of future cross-licensing deals (called "bargaining chips" or "player strategy"). So we distinguish this class of patents that generate strategic value from other nonuse patents. Certainly, some non-strategic nonuse patents will generate some protective value. We focus on a certain class of nonuse patents that generate strategic value on top of conventional protective values.

Table 12.1 Values/benefits accruing to the inventor organization by the modes of use

Mode of uses	Values/benefits accruing to the inventor organization	
	Direct	Indirect/strategic
Internal use		
Integration into own product/ process	Enhanced product competitiveness Reduced manufacturing cost	Enhanced absorptive capacity
External use		
Licensing (unilateral)	Licensing revenue	Increased competition in the product market (-)
Cross-licensing	Saved costs in not negotiating individual license agreements Access to others' technology	"freedom of operation"
Strategic use		
Player strategy	Enhanced position in negotiation for cross-licensing deal	"freedom of operation"
Strategic nonuse		
Fencing	NA	Securing the rent from the core inventions (which is related to but not covered by the focal patent) Heightening entry barriers to a certain product market
Blocking	NA	Increasing competitors' innovation costs Preventing competitors from further innovation
Other nonuse		
Sleeping	NA	Option value Reducing litigation risk

Non-practicing strategic patents are often cited as an example of how patents are abused to slow down innovation. The critics say that the threat of litigation and compensatory awards causes licensing royalties to inflate (Lemley and Shapiro, 2007) and moves firms

to build a protective web of patents to reduce the litigation risks. Also, keeping a large number of patents (especially not practiced patents) creates a huge amount of maintenance costs for a firm. Therefore, many large firms in complex industries support a policy measure to reduce non-practicing strategic patents.[54] This can be called a "pro-user" perspective of patents. On the other hand, if not classified as "misuse" (for the definition and cases of patent misuse, see Hoerner, 1984; Saunders, 2002), non-practicing strategic patents are legitimate. Moreover, they work as an incentive to investing in R&D. In particular, for small firms or start-ups having technology but lacking manufacturing facilities, fencing their core technology using non-practicing patents or blocking competitors from entering into the same technology markets are sometimes the only means by which they can appropriate from investing in R&D. This can be called a "pro-holder" view of patents. This study does not aim to assess whether non-practicing strategic patents are anti- or pro-innovative but aims to identify which characteristics of technology, organization, and invention affect them.

12.1. Hypotheses Development

Strategic nonuse patents are a class of patents that are not commercially exploited but generate strategic rents to the owner of patents by blocking competitor's technological advances or protecting the owners' existing assets. This class of patents covers both "offensive blockade," or thicket builder, and "defensive blockade," or fence builder.

[54] See, for example, amicus curiae filed by Cisco or IBM in KSR International Co. v. Teleflex, Inc. et al. case (Supreme Court 04-1350). Also, see the public comments on the "Hearings on the Evolving Intellectual Property (IP) Marketplace" hosted by the Federal Trade Commission.

Some existing studies distinguish thicket and fence, but in this study we focus on their common characteristics: a defensive or protective role without commercial application.

12.1.1. Size of upstream and downstream assets to protect

From the interviews with managers in the semiconductor industry, Hall and Ziedonis (2001) found that firms with large sunk costs in manufacturing facilities had large incentives to use patents for a safeguard against the threat of costly litigation as well as "bargaining chips" in licensing negotiation. They further showed that the patent propensity indeed increased with the capital intensity. Although they did not show how many of these patents are particularly intended for strategic nonuse, they claimed, based on the interviews, that the increased level of patenting would be somehow related to strategic nonuse. As seen in the patent infringement lawsuit by Polaroid against Kodak, patent infringement sometimes causes the shutdown of an expensive production facility implemented with the infringed technology. In order to prevent this significant loss, firms will tend to avoid infringing others' patents when they build a new production facility. However, in some complex technology areas, it will be hard to identify before a court decision which technology infringes on others' patents. In this case, patents not used for building their own facility but are related to potential litigators will be useful for negotiation. On the other hand, when a production facility is crucial for a firm's competitive advantage and a certain technology is essential for building this facility, the firm will have a large incentive to hinder competitors from building a similar level of production facility by filing for blocking or fencing patents.

In order to identify this relationship empirically, however, we have to look at the comparative aspects of patent uses. In other words, how do the large sunk costs in production facilities affect the propensity of other uses? For internal integration, the larger the sunk costs, the lower the propensity to integrate an individual patented technology into the existing facility because of two reasons: first, firms with higher capital intensity will generally have other options to appropriate the innovation and maintain competitive advantage than patents. First-mover advantage, scale economy of production, and secrecy of production technology all play a role (Cohen, Nelson, and Walsh, 2000; Levin et al., 1987). Second, upgrading the facility requires implementation costs. Also, organizational costs to write a new manual, to train workers, and to optimize the process will accrue in the upgraded facility. Therefore, upgrading the existing facility with an incrementally improved technology will be progressively less beneficial as the size of the facility (and the cost for upgrading) increases. Also, the larger the capital intensity, the smaller the incentive to license out the relevant technology will be. While the potential harm to the expensive facility due to knowledge leakage accompanying the license will increase, this risk factor may not be easily justified ex ante in the licensing agreement. The above arguments lead to our first hypothesis:

Hypothesis 1a. As capital intensity of a firm increases, the propensity of strategic nonuse of its patents will also increase.

A similar argument is applied to upstream technology assets. For contemporary firms in technology-intensive sectors, intangible assets, especially technology assets, are important resources to protect. Some technologies constitute an essential foundation for key products and processes, and some other technologies create direct rents by being traded in the market for technology. Sometimes in the complex technology industries, a single technology will not be enough to secure the rents from a product that can be made only through the combination of multiple technologies. In this case, a firm having a core technology will need a set of other technologies that are complementary to the core technology to fully leverage the power of the core technology. In discrete technology industries, the utility of a core technology will not be secured without having commands over the substitute technologies (Cohen, Nelson, and Walsh, 2000). Therefore, firms having a large portfolio of technology assets will have large incentives to protect it by filing for strategic nonuse patents.

Hypothesis 1b. As the size of technological assets of a firm increases, the propensity of strategic nonuse of its patents will also increase.

12.1.2. Bargaining failure and emergence of a dominant design

Merges (1994) views the existence of blocking patents as a result of bargaining failure between innovators and radical improvers. When both the patentee and the infringer see mutual benefits from a bargain over the right to use the patent, they will reach one. Otherwise, they will face a risk of injunction or a forced bargain on top of costly

litigation fees. Then when do the patentee and potential infringer fail in bargaining? TCE points out transactional uncertainty as a main reason (Williamson, 1981). In the market for technology, major uncertainty stems from an asymmetric view on the prospect and value of technology (Arrow, 1969; Oxley, 1997). Because a single patent document cannot carry all the information required for a potential buyer to assess the value of the technology, it plays a crucial role in bargaining success for both parties to share a common understanding on the technology. This common understanding can be acquired through individual efforts (Cohen and Levinthal, 1990) but also depends on a stage of technology evolution.

Technological development follows a pattern characterized by a sporadic discontinuity and following incremental innovation. Dosi (1982) characterized it as a paradigmatic and normal stage. Abernathy and Clark (1985) and Henderson and Clark (1990) distinguished "architectural innovation" from "incremental innovation." Anderson and Tushman (1990; 1986) take a similar view by distinguishing "technological discontinuities" from incremental innovation. Despite different language and subtle differences among them, there are some common observations across these theories. First, in the phase of technological discontinuities, the value and real impact of innovative technology are hardly foreseeable to the existing firms. Therefore, technological uncertainty is prominent for this type of innovation. This discontinuous technology sometimes creates a new field of technology. Second, after this discontinuous technological innovation acquires a paradigmatic status, lots of incremental innovation follows and populates the field of technology. Technological knowledge in this phase, then, is well-diffused among the

participants and, therefore, the value and utility of incremental innovation become quite well-grounded on the common prospectus. This leads to the following conclusion: as a particular technology becomes more familiar to the players of the technology, technological uncertainty will decrease and, therefore, the odds of bargaining failure will decrease. In summary, we will see a lower propensity of strategic nonuse patents and a higher propensity of licensing as technological familiarity increases.

Besides the transactional point of view, as a dominant design paradigm emerges, a rent that can be generated from a new incremental design will decrease. Competitive advantage will shift to the capacity of mass production and cost efficiency from a design initiative (Teece, 1986). This argument is in line with Schumpeter's description of the "creative destruction" process or Utterback's description of the emergence of a dominant design (Schumpeter, 1942; Utterback, 1994). Also, while wide diffusion of technological knowledge makes competitors' inventing-around easier and a claimable portion of the patent lower (Heller and Eisenberg, 1998; Shapiro, 2000) (and, therefore, reducing the effectiveness of the protective role of a patent), it will lower the costs for integrating the technology in the existing facility. Therefore, strategic nonuse will also be less attractive than internal integration. These arguments lead to the following hypothesis:

Hypothesis 2. As technological familiarity of a patented invention increases, its propensity of strategic nonuse will decrease.

CHAPTER 13. Survey Results

In this chapter, we provide explorative, bivariate analyses of the survey about reasons for patenting and reasons for actual nonuse. The main purpose of this chapter is to present the status of strategic nonuse of patents that the newly conducted survey reveals. So the chapter is not structured to center on the hypotheses we formulated above. Testing hypotheses will be a main focus of the next chapter, where we show the results from multivariate analyses.

The survey asks two questions regarding strategic nonuse of patents. One question asks about intentions of using the patent at the time of the invention. The other question asks about the reasons the patent was not used.

13.1. Reasons for Patenting

The GT/RIETI survey asks why inventors filed for a patent. In particular, the survey asks, in five-point Likert scale with 1 for "not important" and 5 for "very important," how important the following eight reasons were for their patenting: commercial exploitation, licensing, cross-licensing (improving bargaining positions in negotiation), pure defense,

blocking others, preventing inventing-around other key patents, inventor reputation, and firm's reputation.

In addition, we divide blocking patents into two mutually exclusive classes: "player strategy" and "fence strategy." Cohen et. al. (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000) and others (Grindley and Teece, 1997; Hall and Ziedonis, 2001) found that some blocking patents were used as a bargaining chip in cross-licensing deals. This class of patents, named "player patents" by Cohen et. al., is appropriated in a different way from those patents integrated into commercial products or processes. While the latter generates revenues from product markets or technology markets (e.g., by licensing the patents), the former generates strategic rents for the owner to better access to other's technology or secure the freedom of operation.[55] Following Cohen et. al., we define a player strategy as having dual purposes of both cross-licensing and blocking (but in a broad sense, so as to include survey answers for "pure defense," "blocking others," and "prevention").

We interpret "blocking patents" broadly to include both offensive and defensive blockade (Blind et al., 2006). In our survey, we have three "blocking" questions: 1) pure defense (to ensure that the use of your own technology not be blocked by others), 2) blocking patents (preventing others from patenting similar inventions, complements, or substitutes), and 3) preventing inventing-around other key patents of your firm. More precisely,

[55] See an example provided in Rivette and Kline (2000) about how S3, a small graphic chip maker, leveraged its position in a cross-licensing deal with Intel by holding up Intel's developing next-generation processor using the patents acquired from a bankrupt chip maker, Exponential Technologies. Thanks to the resultant cross-licensing, S3 secured the freedom to develop its high-performance graphic chip beyond a siege of Intel's patents.

“blocking patents” in our survey was meant to ask about offensive blockade and “pure defense” and “preventing inventing-around” about a defensive blockade. Initially, we impose a slightly different nuance on each of three questions. For example, “pure defense” aims to prevent others from degrading the patentee’s innovation that may stem from the patented technology. “Blocking patents” aims to prevent others from innovating further based on the patented technology. “Preventing invention-around” aims to prevent others from degrading profitability of the patentee’s other technology but related to the patented technology. These different nuances among three questions, however, seem to be mixed in practice and not to make a difference to some respondents in our survey. Indeed, scores of three variables are highly correlated to each other (Cronbach’s alpha=0.74; tetrachoric correlations=0.53 between pure defense and prevention, 0.73 between pure defense and blocking, and 0.67 between blocking and prevention) and reflect one common latent factor. Therefore, we use “blocking patents” in a broad sense to include pure defense and prevention, while we used “blocking patents” narrowly in the survey.

On the other hand, a “fence” patent is a subclass of blocking patents that are not intended for licensing or bargaining chips. This class of patents benefits the owner in a different way from the player patents in that it 1) prevents competitors from going ahead in the innovation race,[56] 2) protects other core technologies owned by the firm from being

[56] An exemplary case is “Fleming valve” patent by the Marconi Wireless Telegraph company which refused to license the competitor, De Forest company, and blocked developing improvement technology. (Marconi Wireless & Tel. Co. v. De Forest Radio Tel & Tel. Co., 236 F. 942 (S.D.N.Y. 1916)). The stymie in developing radio technology brought forth by fragmented patents was finally resolved by introduction of a consortium, RCA. (Merges, 1994).

invented-around,[57] or 3) reduces future litigation risk (Lemley and Shapiro, 2005). This class of patents is close to a "defensive blockade" in Blind et. al.'s (2006) usage. Following Cohen et al. (2002), we define fence patents as those patents filed for blocking purposes but neither for licensing nor for cross-licensing. Thus, fence patents and player patents are mutually exclusive subsets of defensive patents.[58]

Figure 13.1 illustrates the proportion of "important" or "very important" for each reason for patenting. Not surprisingly, commercial exploitation (82.3%) is the most important reason to patent. Consistent with the findings from the Carnegie Mellon survey, blocking is reported as one of the most important reasons for patenting. Offensive blocking (46.2%) is the second highest and pure defense (44.9%) the third highest reason to patent in the survey. Also, about one-fifth of the patents in the survey were filed to prevent inventing-around. Overall, 71.6% (=1180/1647) of inventors in the sample reported that at least one of the three blocking purposes were important or very important for their patenting. As for the two external commercialization strategies, licensing and cross-licensing, about a quarter and about half (50.2%) of inventors in our sample, respectively, reported them as important or very important reasons for patenting. For player strategy and fence strategy, 17.1% and 35.6% of patents in the survey, respectively, were reported as important or very important for patenting.

[57] A famous case is a color proofing process technology invented by Roxy N. Fan, a scientist at Du Pont at the time of invention, and subsequently patented to Du Pont. The Fan patent was not commercially exploited by Du Pont but used for blocking out a competitor from the color proofing market in which Du Pont's competing technology, Cromalin process, took 90 percent of the share (E. I. du Pont Nemours & Co. v. Polaroid Graphics Imaging, Inc., 706 F. Supp. 1135, 1139 (D. Del.). aff'd. 887 F.2d 1095 (Fed. Cir. 1989)) (Turner, 1998).
[58] Note, however, that they are not mutually exhaustive because fence strategy is one more constraining condition, licensing, than player strategy.

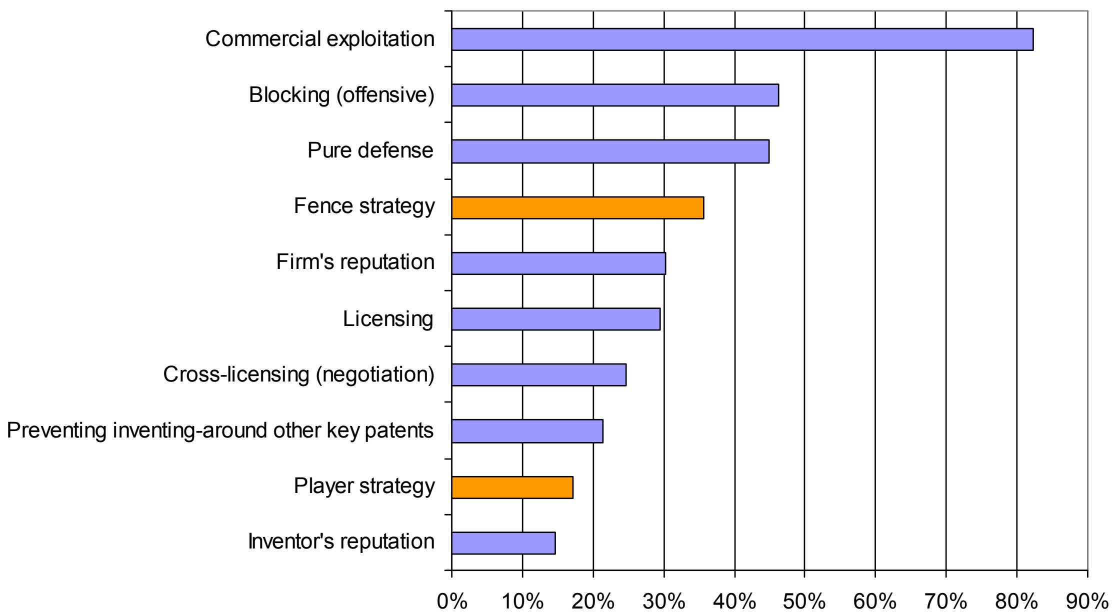

Figure 13.1 Reasons for patenting

Note: fence and player strategies were constructed from a combination of multiple reasons as described above

Patenting strategy varies significantly across sectors. Figure 13.2 shows the share of the patents giving high importance to each reason within the sector. Again, commercial exploitation is the most prominent reason for patenting. The second highest reason is offensive blocking (in Chemistry, Process Engineering, Mechanical Engineering, and Consumer Goods and Construction) or "pure defense" (in Electrical Engineering and Instrument). Process Engineering (which includes chemical engineering, textiles, paper, printing, food process, etc.) shows the highest share of blocking (54.3%) and preventive reasons (28.4%) among six sectors. The most prominent differences among sectors occur in cross-licensing. Consistent with the previous literature (Cohen, Nelson, and Walsh,

2000; Grindley and Teece, 1997; Hall and Ziedonis, 2001), Electrical Engineering (39.7%) and Instruments (27.2%) show a higher share of cross-licensing while Mechanical Engineering (10.7%) and Consumer Goods and Construction (2.5%) show a very low rate. Also, player strategy shows a similar pattern with cross-licensing while fence strategy shows an offset-like pattern with cross-licensing. This pattern is roughly consistent with the results from the Carnegie Mellon survey, which observed that player strategy was more prominent in complex industries (such as electronics, instruments, and transportation equipment) than in discrete industries (such as food, textiles, drugs, and metals) and that fence strategy was more prominent in discrete industries (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000).

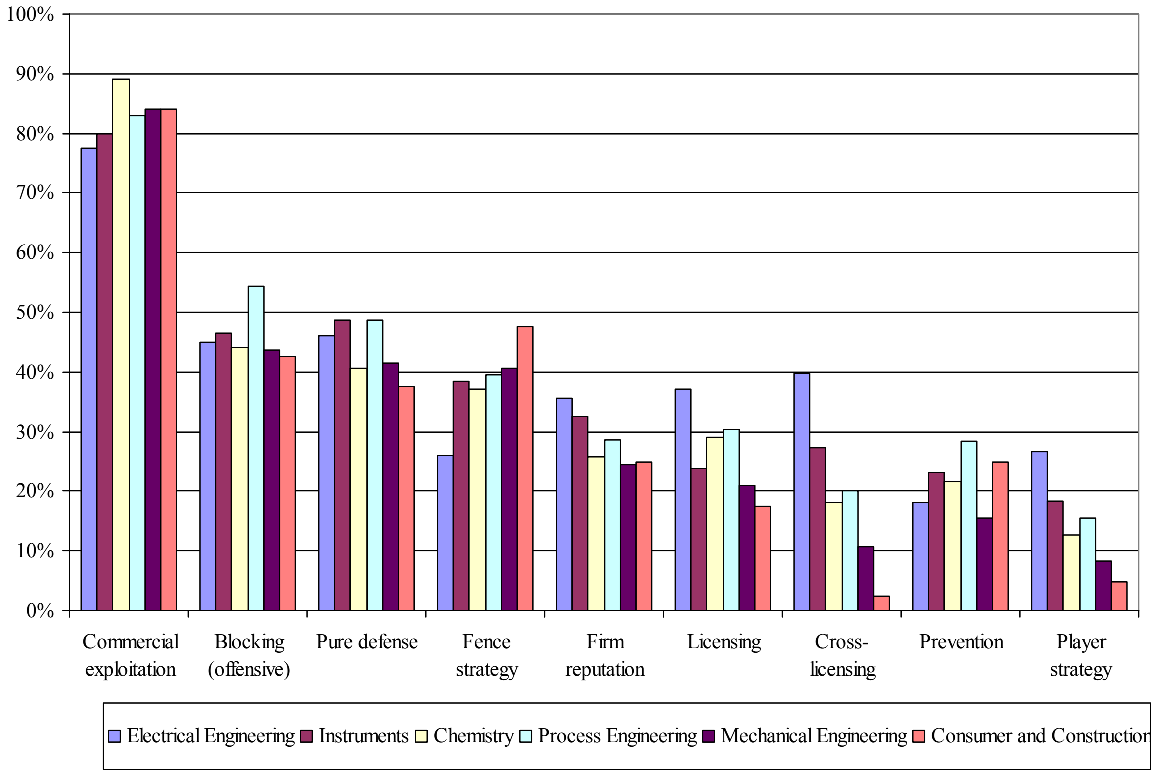

Figure 13.2 Share of patents giving a high importance to the reasons of patenting by industry

Next we examine the differences in motives for patenting by firm size and the complexity of technology. The survey shows significant differences in the reasons for patenting by the size of firms to which the respondent belonged at the time the invention was made. In our survey, the share of inventors giving high importance to commercial exploitation, licensing, and firm's reputation is statistically significantly higher in small firms than large firms. While almost 43% of the patents from small firms are filed for licensing, only 27% of large-firm patents are filed for licensing. On the other hand, cross-licensing is reported as an important reason for patenting more in large firms (27%) than in small

firms (17%). A higher share of patents from large firms are for cross-licensing, player, and fence strategies.

In order to examine whether the reasons for patenting differ by the characteristics of technology, we break down the technological areas into 30 subgroups. The first four columns of Table A. 8 in Appendix E characterize each technology in four dimensions: complexity of technology, importance of complementary technology, importance of patents, and importance of short lead-time. They are all constructed from the survey. Complex technology areas are identified using the survey. The GT/RIETI survey asks the inventors "how many domestic patents are jointly used in the commercial application of the invention." It provided eight categories: 1, 2 to 5, 6 to 10, 11 to 50, 51 to 100, 101 to 500, 501 to 1,000, and more than 1,000 patents. We averaged the median values over 30 subgroups of technologies and constructed a variable, "technological complexity." Then a dichotomous variable, "complexity of product technology," is coded 1 if the technological complexity of the subclass to which the focal patent belonged was higher than the median value of technology complexity. The complex technologies classified in this way include information technology, semiconductors, telecommunication, electronics, biotechnology, and chemical engineering. The non-complex (or discrete) technologies include textile, pharmaceuticals, agriculture and food, construction, and transportation technologies.[59] Complexity of technologies calculated in this way is roughly consistent

[59] The other three variables are all constructed from the survey questions about the strength of appropriability conditions. The GT/RIETI survey asks the inventors to rate, in a five-point Likert scale, the importance of eight appropriability conditions for protecting a firm's competitive advantage regarding commercializing the invention. The importance of complementary technology is constructed from the maximum value of two items: "[f]irst mover's advantage in follow-up R&D (developing complementary technologies and the patent portfolio)" and "[c]ollaboration with other firms having complementary technologies." The importance of patents and the importance of short lead-time are constructed from the

with a simple dichotomy based on the qualitative studies (Cohen et al., 2002; Cohen, Nelson, and Walsh, 2000; Kusunoki, Nonaka, and Nagata, 1998).

This characteristic of industry has discriminating effects on the patenting strategies as indicated by statistically significant differences for almost all reasons of patenting in the right pane of Table 13.1. Consistent with the findings of Cohen et al., player strategy is adopted significantly more in complex technology areas, while fence strategy is adopted more in discrete technology areas. This seems to stem from the prominence of cross-licensing in complex technology. Two of the three blocking purposes (pure defense and prevention) show no significant differences by complexity of technology. Offensive blocking is slightly more favored in discrete technology.

reported value of each corresponding item. Similar to the technology complexity variable, we then average these values over 30 subgroups of technology and dichotomize them by industry median, respectively.

Table 13.1 Share of patents giving a high importance to the reasons for patenting by the size of firms and the complexity of technology

	Firm size				Complexity of technology			
	N	Small & medium	Large	Pearson chi2(1)	N	Discrete	Complex	Pearson chi2(1)
Commercial exploitation	1688	89.1	80.8	9.7***	1689	86.1	79.4	12.6***
Blocking (offensive)	1649	45.2	46.4	0.1	1650	49.7	44.1	5.0**
Pure defense	1655	41.4	45.6	0.2	1656	44.8	45.2	0
Fence strategy	1637	30.6	36.5	3.1*	1637	41.8	31.5	18.3***
Firm's reputation	1663	37.7	28.9	7.5***	1664	25.4	33.5	12.5***
Licensing	1646	42.7	26.9	24.9***	1646	27.1	30.7	2.4
Cross-licensing (negotiation)	1639	16.9	26.4	9.9***	1639	16.5	30.9	43.5***
Preventing inventing-around other key patents	1636	22.5	21.2	0.1	1637	22.5	20.8	0.7
Player strategy	1634	13.5	18.1	3.0*	1634	12.0	21.2	23.0***
Inventor's reputation	1647	14.7	14.6	0	1648	12.0	16.7	6.7**

*** p<0.01, ** p<0.05, * p<0.1

Above we show that profiles of patenting strategies vary by firm size and characteristics of industry (i.e., technological complexity of products). In order to further understand how the different profiles of patenting strategies between large and small (and medium) firms vary by industry, we cross-tabulate the share of importance of each patenting strategy by the size of firms and by complexity of product technology.

Table 13.2 shows the relationship of three strategies (detail statistics are presented in Table A. 9 of Appendix E). The table reads as follows: the share of patents filed because of the importance of player strategy is larger for large firms than for small or medium firms in complex technology. Licensing is unanimously favored by a larger share of small and medium firms than large firms in all technologies. Fence and player strategies show discrepancy by technology between large and small firms. Both fence and player strategies are more adopted by large firms overall. However, the differences are statistically significant in discrete technologies for the fence strategy and in complex technologies for the player strategy. This observation is largely consistent with the arguments that view the roles of patents as protecting the existing firm assets (Hall and Ziedonis, 2001; Ziedonis, 2004). More interestingly, player strategy is more favored by small firms in pharmaceutical, polymers, and biotechnology (although the difference is not statistically significant for biotechnology due to small N). On the other hand, small firms favor the fence strategy in electrical engineering technologies. This implies that, separate from the "assets-at-risk" argument, there may be a fundamental discrepancy of R&D and patenting strategy between small and large firms according to the characteristics of industry.

Table 13.2 Reasons to patent by firm size and by complexity of product technology

Small & medium; large	Discrete		Complex			All
	all	Pharm & Poly	all	Bio	EE	
Licensing	>***	>***	>***	>	>	>***
Fence strategy	<*	<	<	<	>*	<*
Player strategy	>	>***	<***	>	<***	<*

Note: Pharm & Poly: Pharmaceuticals & Polymers; Bio: Biotechnology; EE: Audio/Visual, IT, Telecom & Semiconductors
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In this section, we presented a similar finding by Cohen et al. (2002) that player and fence strategies account for a substantial share of firms' patenting, and they are, indeed, subject to the complexity of product technology. In doing so, we applied an advanced measure of the complexity of product technology. We presented novel findings that patenting strategy differs by the size of firms. Moreover, the analysis shows that patenting strategies from different sizes of firms are heterogeneous across industry. In particular, diverging patenting strategies of firms according to their sizes are prominent (and somewhat distinct in their effects from the rest) in chemical and pharmaceutical industries.

13.2. Reasons for Nonuse

In this section we present the results for the reasons a patent has not been commercially exploited. In our survey, we asked for the nonuse patents reasons a patent has not been used (Figure 13.3). Among 1,672 patents from firms that reported their modes of uses and/or the reasons for nonuse, 769 patents (46.0%) were not used at the time of the survey. A dominant share of firms were still exploring the commercial possibility (59.3% of nonuse patents or 27.3% of all reported patents) or used internally as a research tool (8.0%). However, our survey reveals that a significant share of nonuse patents was strategically exploited for blocking, either offensively (15.2%) or defensively (10.3%). Offensive and defensive blocking, together, account for 16.7% of patent usage. The other reasons for nonuse include a family that fall into obsolete patents (technology or market shift, downsized or failed line of business accounting for 18.9% together), a family related to lack of sponsors to commercialize the technology (licensees or financiers accounting for 5.2% together), or other technological problems (low technical level, delay in developing complementary technologies, or lack of technologies for application, accounting for 11.6% together).

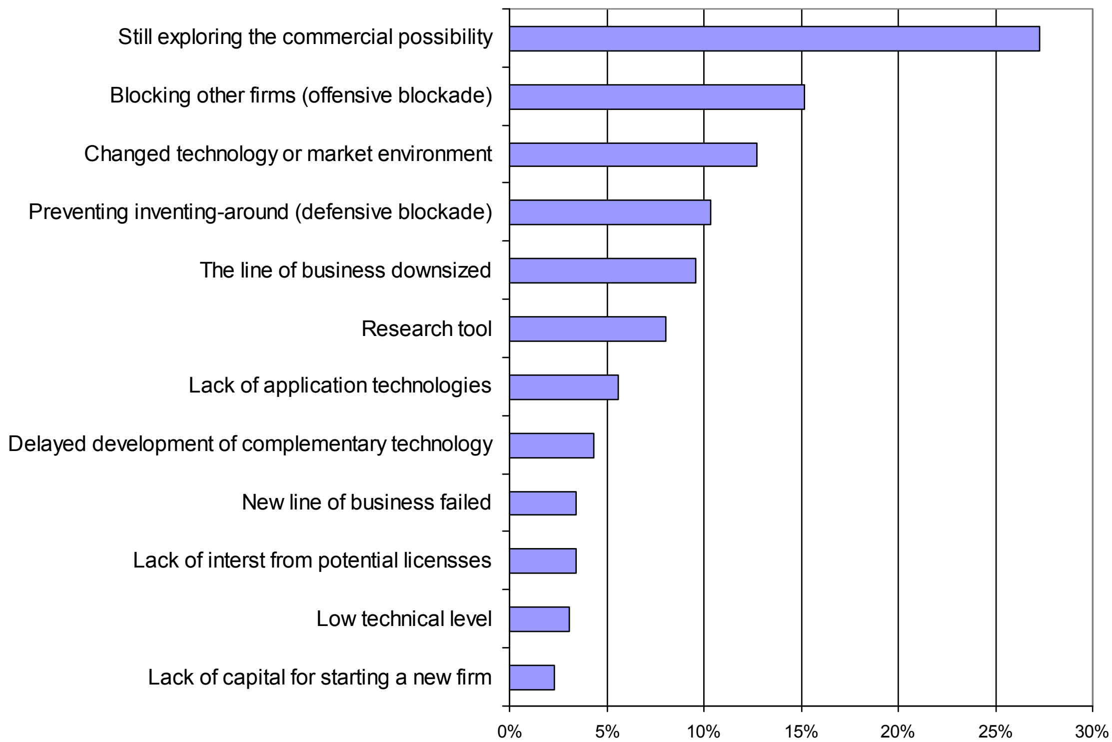

Figure 13.3 Reasons for nonuse (N=1672)

Among the various reasons for nonuse, we particularly focus on three families of reasons: 1) strategic nonuse family including "blocking other firms" and "preventing inventing-around, 2) obsolete patents family including technology or market shift, downsized or failed line of business, and 3) non-sponsor patents family including "lack of capital for starting a new firm" and "lack of interest from potential licensees."[60] The strategic nonuse family refers to blocking patents, both offensive and defensive. The latter two families refer to a proven failure of commercialization (obsolete patent family) and a

[60] The results of an exploratory factor analysis based on tetrachoric correlations are consistent with this grouping.

potential institutional failure for commercialization (non-sponsor patents that failed to recruit investors for commercialization).

The economic and technological values[61] of strategic nonuse patents are lower than commercially used patents but higher than obsolete patents (Table 13.3). However, strategic nonuse patents are evaluated almost same level as non-sponsored nonuse patents.

Table 13.3 Value of nonuse patents

	Economic value		Technological value	
Mode of (non)use	N	Mean (percentile)	N	Mean (percentile)
Any commercial use	748	60.02	757	65.49
Strategic nonuse	225	44.86	236	52.49
Strategic nonuse (broad)	337	46.09	359	53.50
Lack of sponsors	71	45.70	76	53.03
Obsolete patents	259	40.97	276	49.54
Total	1339	53.71	1388	60.32

Table 13.4 shows the value (both economic and technological) of strategic nonuse patents in the sample by firm size. In the sample, the value of strategic nonuse patents from large firm are lower than those from small or medium firms.

[61] In our survey, we ask the inventor to assess the technical significance and economic value of the invention relative to other technical developments in the field during the year when the focal patent was applied for. We used the midpoint of each category (top 10%; 25% (but not top 10%); top 50% (but not top 25%); and bottom half).

Table 13.4 Value of strategic nonuse patents by firm size

	Economic value		Technological value	
Firm size	N	Mean (percentile)	N	Mean (percentile)
Small & medium	13	49.81	16	63.91
Large	212	44.55	220	51.66
Total	225	44.86	236	52.49

Next, we examine how the share of the three reasons is associated with a set of characteristics at invention-, firm-, and technology-level. The criteria examined are firm size, complexity of technology, the appropriability regime of patents, collaboration (whether or not the invention involves any external collaborator), type of innovation (product v. process), and inventor unit (whether the inventor belonged to a manufacturing unit at the time of invention). The summary results are presented in Table 13.5.

While the share of strategic nonuse and obsolete patents is significantly higher in large firms, the share of non-sponsor patents is higher in small firms. The previous chapters show that large firms are more likely to use patents for commercial purposes, especially via internally integrating them. The survey shows that large firms not only have larger numbers of strategic nonuse patents but also filepatents for a larger number of proven failed technologies. This finding implies two things. First, patent propensity may be higher for large firms than for small firms. Large firms file for patents even such technologies that have no immediate commercial uses or marginally superior technologies. Second, particularly for obsolete patents, large firms may have broader capabilities for which they can apply even marginally superior technologies.

Next, the survey shows that there are more obsolete patents in complex technology than in discrete technology. This may reflect the short life cycle of technology in complex technology areas. Interestingly, collaborative inventions and inventions tightly coupled with manufacturing processes are lower in the rate of failure. Recall that we showed that the patents of these characteristics are also more likely to be commercialized (internally). It seems that collaboration and tight coupling to manufacturing process in the invention process will not only have positive effects on commercialization but also reduce negative effects of failure.

Patent strength and the degree to which the invention is linked to the existing capabilities (i.e., competence-destroying or enhancing) do not make obvious differences on any of these reasons of nonuse. Other appropriability conditions (such as the importance of complementary technology or the lead time advantage) do not make a significant difference for these reasons, either.

Table 13.5 Share of three types of nonuse patents by several characteristics

Criteria	Value of criteria	Strategic nonuse patents	Strategic nonuse patents (broad)	Obsolete patents	Lack of capital or licensee
Firm size (N=1672)	Small and medium	7.6	14.9	12.1	10.0
	Large	18.3	27.3	20.5	4.2
	Chi-square	17.3***	17.4***	9.6***	14.9***
Complexity of product technology (N=1672)	Discrete	17.6	25.9	15.7	3.7
	Complex	16.1	25.2	21.6	6.0
	Chi-square	0.7	0.1	9.1***	4.5**
Importance of patents for appropriation (N=1670)	Low	14.8	24.2	17.8	5.9
	Hi	18.3	26.6	20.4	4.5
	Chi-square	3.7*	1.2	1.7	1.6
Collaboration (N=1665)	No	17.2	26.9	21.2	4.7
	Yes	15.3	21.6	13.5	5.9
	Chi-square	0.8	4.7**	12.5***	1.0
Competence-enhancing or destroying (N=1665)	Enhancing	19.1	26.1	19.5	4.4
	Destroying	14.8	24.9	19.1	5.6
	Chi-square	5.2**	0.3	0.0	1.3
Inventor unit (N=1656)	Non-manufacturing	17.0	26.1	19.9	5.3
	Manufacturing	14.3	20.0	12.1	3.6
	Chi-square	0.7	2.5	4.9**	0.8

*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 14. Hypotheses Tests

14.1. Data

The estimation sample is based on the GT/RIETI survey and supplementary data sources including PATSTAT, the USPTO database, and COMPUSTAT as described in Chapter 4. Out of 1,919 valid responses, 1,807 cases are from firms. After deleting listwisely the cases that have missing values on our covariates, we have 1,241 complete cases for estimation.

14.2. Variables

This section introduces variables used for multivariate analysis.

14.2.1. Dependent variables

Our dependent variable, "strategic nonuse" is constructed using the GT/RIETI survey. A binary variable, "strategic nonuse," is coded 1 if the patent was used for "blocking other firms" or "preventing inventing-around" and not used for any commercial purpose. We also construct a second measure of strategic nonuse by fusing information on the reasons for patenting with the reasons of actual nonuse. In the survey, some patents filed for strategic purposes are reported to end up with some other uses. About a half of them

reported to “still explore commercial opportunities.” They may indeed play a blocking or fencing role while waiting for commercial applications. Therefore, we identified those patents of high intention for strategic nonuse at the time of patenting additionally as strategic nonuse patents. A broadly defined strategic nonuse is coded 1 if the original variable is one or if nonuse is true and the reasons for patenting for blocking or prevention are reported important or very important. The strategic nonuse is different from fence or player strategies. Recall that player strategy is more than blocking. It is designated to using patents to improve a position in (cross-)licensing negotiation. Strategic nonuse as defined in this section excludes the patents used for licensing or cross-licensing. It is actual nonuse targeted for blocking competitors or preventing other core inventions owned by the holder of the strategic nonuse patents. Therefore, strategic nonuse includes all fence patents but a part of player patents.

14.2.2. Explanatory variables

Capital intensity

Following Hall & Ziedonis (2001) and Ziedonis (2004), we measure capital intensity using the deflated book value (constant U.S. dollars in 2000) of property, plant, and equipment divided by number of employees. In order to mitigate yearly fluctuation and reduce missing values, we use a three-year running average centered on the filed year of a focal patent. Main data sources are COMPUSTAT North America–Fundamentals Annual and COMPUSTAT Global–Fundamentals Annual.[62] For a few firms, we directly find the data from their web sites. In the sample, about a quarter of firms are either private or

[62] We use consolidated financial reports. Therefore, many subsidiaries in our sample are regarded as a parent company whose financial information is available.

foreign whose financial information are not available in either the COMPUSTAT or alternative sources mentioned above. They are coded as a dummy variable named "dummy for missing capital intensity."

Technological assets

We use patent stock as a proxy for technological assets of a firm. Patent stock is calculated as the number of granted U.S. patents assigned to the first assignee in the focal patent and filed before the filed year of the focal patent. Patent stock of firm i for a focal patent filed in year t is:

$$PS_{it}=PS_{i\,(t-1)}(1-\delta)$$

where δ represents the constant depreciation of knowledge which is set to 15% following the previous studies (Grimpe and Hussinger, 2008; Hall, 1990).

Similar to the way we construct the capital intensity, subsidiary firms are consolidated into their ultimate parents. Patent stock of merged and acquired firms is also consolidated into the merger. We use the April 2008 version of the "EPO Worldwide Patent Statistical Database" (henceforth, PATSTAT) provided by the European Patent Office. There are two advantages using PATSTAT for this purpose. First, PATSTAT provides relational tables and an SQL interface for the bibliometric information of the U.S. patents, which make data extraction much easier than other available data sources. Second, PATSTAT provides standard identification numbers of assignees, which corrected many typos and

spelling differences. We further cleaned the data by manually searching and correcting the list of assignees in the sample.

Component familiarity

We operationalize technological familiarity using the familiarity index of technological components suggested by Fleming (2001). "Component familiarity" captures the degree to which a patentee is familiar with the technological components that were used in his patent. The basic assumption is that as a technology matures (therefore, the population of technological artifacts increases), technological trajectories based on this technology become more foreseeable (Dosi, 1982). Component familiarity, as suggested by Fleming, averages the number of patents previously assigned to the same technology classes of the focal patent and applies a knowledge attenuation factor by temporal distance between the focal patent and the referred patents. He has empirically shown that component familiarity is in inverted-U relationship with the uncertainty of utility of the patent as measured by the variation of forward citation counts.

In order to construct this variable, first we count the number of U.S. patents filed from 1976 to 1999 in each technology class and match them to the subclass of a patent in our sample.

Component familiarity for patent i =

$$\frac{1}{N_{C_i}} \sum_{c_j \in C_i} \sum_{\substack{\textit{all patents k filed} \\ \textit{from } 1976 \textit{ to } 1999}} 1\{\textit{patent k assigned to subclass } c_j\} \times \textit{kattenuation}_k$$

where $C_i = \{\text{patent subclass assigned to patent i}\}$,

c_j = patent subclass identifier,

N_{C_i} = number of different patent subclasses assigned to patent i,

and knowledge attenuation factor, $kattenuation_k$ =

$$\exp(\frac{\text{temporal distance of patent k}}{\text{time constant of knowledge loss}}),$$

where temporal distance of patent k=

4.5 if patent k was filed from 1995 to 1999

9.5 if patent k was filed from 1990 to 1994

16.5 if patent k was filed from 1976 to 1989

Time constant of knowledge loss is set to 5 following Fleming (2001). We rescaled component familiarity by dividing it by 1000.

Patent effectiveness

In order to test the effects of patent effectiveness at the technology or industry level, we use two measures. One measure is constructed from the question of the GT/RIETI survey addressing patent strength in maintaining competitive advantage of the commercialized patented inventions. We aggregate the answer to this question in a five-point Likert scale at technology class. Because this question was directed to the inventors whose patents were commercialized, this may not properly represent overall effectiveness of patents. Thus, we also adopt the patent effectiveness measure provided by the Carnegie Mellon survey (Cohen, Nelson, and Walsh, 2000). We averaged the median value of the original CMS measure of patent effectiveness at International Standard of Industry Code (or ISIC) over four-digit NAICS code of assignee firms in our survey. About 16% of cases for which we could not find NAICS code were dummy-coded as “Missing patent effectiveness.”

14.2.3. Controls

We included several variables to control for alternative factors that may influence the propensity of strategic nonuse.

Fragmented ownership of a patent

Ziedonis (2004) showed that the patenting propensity of firms in the semiconductor industry increased as the patenting ownership was more fragmented. She suggested that a large portion of the increased patenting would be ascribed to the patents filed for strategic nonuse. Although she did not prove the direct relationship between the increase of strategic nonuse patents and the fragmentation in that paper, she had provided anecdotal evidence on that in her previous paper with Hall (Hall and Ziedonis, 2001). Adapting Ziedonis's fragmentation index at firm level to patent level, we constructed a "patent fragmentation index." In the United States, an invention is patentable only if differences between the claimed invention and the prior art should not be "obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains" (35 U.S.C. 103). Prior art is pertinent and applicable to the patent and has "a bearing on the patentability of any claim of the patent" (37 C.F.R. 1.501) as assessed by the applicant, examiners, or a third party.[63] Therefore, in order to fully utilize the patented invention, the executor of the patent (e.g., the owner or a licensee) would need access to the entirety or a part of prior arts. The patent fragmentation index measures how widely the prior art that is beyond a command of the owner of the focal

[63] For the discussion about citation of prior art, see a recent paper by Alcacer, Gittelman, and Sampat (2009)

patent is distributed. Fragmentation index of a patent k assigned to firm i_k is constructed as

$$\text{FRAG}_\text{k} = 1 - \sum_{j_k \neq i_k} \left(\frac{NBCITES_{j_k}}{NBCITES_k - NBCITES_{i_k}} \right)^2,$$

where j_k refers to each unique assignee that is cited by a patent k assigned to firm i_k and whose patent was filed after 1984. $NBCITES_k$ is the number of the U.S. patents cited by patent k, $NBCITES_{i_k}$ the number of the self-cited U.S. patents, and $NBCITES_{j_k}$ the number of the U.S. patents cited by patent k and assigned to j_k. We consider the cited patents filed only after 1984 because most patents filed before 1984 must have expired by the time the focal patents of the sample was granted and, therefore, would not claim for ownership rights. We also tested the fragmentation index without restriction of filed year of cited patents to find no difference. The patent fragmentation index indicates the difficulties (or costs) of bargaining that may be required for full access to the subject technologies claimed in the patent.[64]

Strength of patents and appropriability regime

[64] The patent fragmentation index measures how widely the ownership of technological components that might be need to use the technology claimed in the focal patent. This is different from the complexity of product technology which measures how many technological components are required to make a final product. For example, if one technological component that constitutes a technologically complex product is built on proprietary prior arts or based on discrete technologies, then the fragmentation index will be low while complexity index of product technology high. Correlation coefficient between these two measures in the sample is very low (-0.01) and not statistically significant (Table A. 10).

We control the strength of patents and the regime of appropriability at both patent-level and technology- and industry-level. The measures for the strength of patent include complexity of technology as a count of different technology subclasses assigned to the patent and number of claims. At the technology level, we control the primary technology fields as identified in the first IPC. Because the semiconductor industry is known to be prosperous in blocking patents, we control the semiconductor industry as identified by the primary NAICS codes (333295, 333994, 334411, 334413, 334515, and 335999) of assignee firms. We also control the strength of patent at the industry/technology level. The first measure is constructed from the survey question asking about the strength of appropriability of patents for commercialization. This variable is aggregated at 30 technology classes. However, this variable has some problems. The variable is constructed from the assessment from the respondents who answered that they used the patents for internal commercialization. This limitation may distort the overall effectiveness of patents for appropriating innovation. Hence, we tested an alternative measure. The patent effectiveness measure provided by the Carnegie Mellon survey (Cohen, Nelson, and Walsh, 2000) was well examined in the literature and showed consistent results. We matched the CMS patent effectiveness measure to the primary industry classification (NAICS) and assigned corresponding values, separated by product and process, to the observations of the sample. Although overall reliability of this measure is believed to be higher than the first measure, it also has problems, such as missing NAICS value, missing on product/process distinction, and errors generated by transformation and aggregation. We additionally control a dummy for missing values on this variable.

Openness of innovation process

We control the openness of the innovation process by including two measures: diversity index of external collaboration and the breadth of openness. The first measure, constructed from the survey, is the count of different external entities with which the inventor organization had collaborated during the invention process. The breadth of openness is a similar measure used by Laursen and Salter (2004) constructed from the survey by counting the different channels of external knowledge sources.

We also control the technological value of patents, the ownership of complementary assets (as measured by whether the inventor belongs to manufacturing units), complexity of product technology, firm size (as measured by the number of employees),[65] whether there is an immediate demand for the technology, size of the invention projects (number of inventors and man-month), product/process, and basic-applied orientation of the inventor. Sample statistics are presented in Table 14.1.

[65] Correlation coefficient between the firm size and the patent stock is 0.59 and statistically significant, which falls below the 0.70 threshold and, indeed, is discriminatory (Cohen et al., 2003).

Table 14.1 Sample statistics (N=1241)

Variable	Mean	Std. Dev.	Min	Max	Data source
Strategic nonuse (narrow)	0.174	0.379	0	1	Survey
Strategic nonuse (broad)	0.261	0.439	0	1	Survey
Explanatory variables					
Patent effectiveness (CMS)	32.877	7.266	16.400	50.200	CMS
Missing patent effectiveness	0.157	0.364	0	1	CMS
Strength of appropriability of patents	3.748	0.294	2.875	4.222	Survey
Capital intensity (M$/employee)	0.076	0.131	0	1.908	COMPUSTAT
Dummy for missing capital intensity	0.259	0.438	0	1	COMPUSTAT
Ln(patent stock)	5.473	2.740	0	9.865	PATSTAT
Component familiarity (/1000)	0.085	0.154	0.000	2.489	USPTO
Controls					
Fragmentation index	0.678	0.283	0	0.979	PATSTAT
Large firm (employees >500)	0.861	0.347	0	1	Survey & Patent
Inventor in manufacturing unit	0.084	0.277	0	1	Survey
Competence-destroying invention	0.573	0.495	0	1	Survey
Complexity of product technology	0.584	0.493	0	1	Survey
Breadth of openness	4.666	2.899	0	10	Survey
Diversity index of collaboration	0.434	0.863	0	8	Survey
Technological value	2.218	1.068	1	4	Survey
No immediate demand	0.222	0.416	0	1	Survey
% Basic R&D (/100)	0.079	0.172	0	1	Survey
Product invention	0.510	0.500	0	1	Survey
Man-month (normalized)	0.182	0.229	0.005	1	Survey
Number of inventors	2.797	1.916	1	16	Patent
Complexity of technology (# USPC)	4.452	3.538	1	30	Patent
Number of citations to the U.S. patents	17.697	24.478	0	399	Patent
Number of claims	22.922	15.585	1	181	Patent
Age of invention (months)	68.874	12.002	37	92	Patent
Semiconductor industry	0.069	0.254	0	1	COMPUSTAT
Electrical engineering	0.257	0.437	0	1	Patent
Chemistry, pharmaceuticals	0.239	0.427	0	1	Patent
Process eng, special equipment	0.135	0.342	0	1	Patent
Mechanical eng, machinery	0.132	0.339	0	1	Patent
Consumer goods & Construction	0.028	0.166	0	1	Patent

14.3. Multivariate Analysis

Because our dependent variable is binary, we use a probit regression model. Column 1 through 6 of Table 14.2 show the estimates using the narrowly defined strategic nonuse as dependent variable and column 7 with broadly defined strategic nonuse for robustness checks.[66] First, we estimated binary probit regressions without patent effectiveness variables (column 1) and added two different measures of patent effectiveness (columns 2 and 3). Column 2 was estimated with strength of patent appropriability (aggregated at 30 technology groups) constructed from the survey and column 3 estimated with patent effectiveness measure (aggregated at four-digit primary NAICS) constructed using the Carnegie Mellon survey (Cohen, Nelson, and Walsh, 2000).

Next, in order to examine the discriminating effects of independent variables in relationship with other modes, we estimated multinomial logistic models (columns 4 through 6). The reference outcome for the multinomial logistic models is "strategic nonuse," and compared outcome levels are other nonuse (named "sleeping"), internal commercialization, and external commercialization. The four outcomes compared satisfy the IIA assumption as shown by the Small-Hsiao tests. Also, both Wald and Likelihood-ratio tests reject the null hypothesis that strategic nonuse can be combined with any other outcome categories. This indicates that strategic nonuse patents are not only a meaningful category theoretically but also a valid category empirically. Indeed, the multinomial logistic regression reveals several important aspects to further our understanding on the drivers of strategic nonuse patents. For example, by treating strategic nonuse distinctively

[66] We estimated all models twice using the two dependent variables. All the estimations did not show notable differences between two definitions, except for the capital intensity in the probit regressions. So we report the estimations based on the narrowly defined strategic nonuse as a standard.

from internal use, we could better understand the diverging effects of firm assets and patent effectiveness on them. By treating strategic nonuse distinctively from external use, we could test the bargaining failure arguments. Furthermore, the multinomial logistic regression reveals the distinctive effects of the technology development cycle on strategic nonuse compared to nonuse and internal use as well as external use. All estimated models show acceptable range of goodness-of-fit statistics (log likelihood and chi-square statistics are reported at the bottom of the table). In order to check the effects of dummy-coding of one of the independent variables (capital intensity), we ran the models for the complete set of the sample after removing the observations missing the capital intensity. There is no change in the basic relationship from the presented models.

Turning to our central variables of interest, as expected from Hypothesis 1a, capital intensity is significantly and positively associated with the propensity of strategic nonuse when it is broadly defined (column 7). As the capital intensity increases by $1 million above its mean, the probability of a patent being strategic nonuse increases by 17.1 percentage points holding all the other variables at their means or modes. However, when using the narrow definition of strategic nonuse, the relationship turns marginally insignificant (but still keeping its sign positive). So we have limited support for Hypothesis 1a. Looking at the result of multinomial regressions, while the distinctive impact of capital intensity on the strategic use against sleeping patents is not clear (column 4), it is distinctive against “internal use” (column 5). Compared to internal commercialization, increase of the capital intensity by $1 million above its mean lowers the probability of strategic nonuse by 46.3 percentage points, holding all the other

variables at their means or modes.[67] These results, in combination, make two interpretations possible. First, if we assume that even sleeping patents may play some protective roles, then we cannot tell whether the effects of capital intensity on strategic nonuse are related to the protective reason or to the use-suppressing reason. Second, if we assume no protective roles of sleeping patents, then our results imply that we cannot confirm the existence of protective roles of strategic nonuse patents, either. In this case the reason capital intensive firms file more strategic nonuse patents is more likely because they are left out of the internal commercialization process. In other words, although many strategic nonuse patents in capital intensive firms are internally commercializable, the higher level of costs integrating them into larger and probably more complex plants and facilities had suppressed their uses. So the latter case will be a byproduct of ordinary innovation activities.

As predicted by Hypothesis 1b, the estimates of patent stock are significant and positive. This effect is net of firm size because we separately control firm size. The results read that firms having larger technological assets to protect are more likely to have strategic nonuse patents. Looking at the multinomial logit models, patent stock has a significant and positive impact on the propensity of strategic nonuse compared to internal commercialization (column 5) but no significant impact compared to sleeping patents or external commercialization (columns 4 and 6). This indicates that, similar to the

[67] The main results are robust against missing values of this variable. A multinomial logistic regression run after excluding the missing values on the capital intensity shows no notable differences from the main results in signs, magnitude, and significance of coefficients on the key variables. Also, the relationships of the dependent variable and other key independent variables are held when the capital intensity variable is dropped from the regression.

arguments we made for capital intensity, we cannot isolate the protective effects from the use-suppression effects.

Finally, our bargaining failure and dominant design hypothesis is well supported by the empirical estimation. The coefficient on component familiarity is highly significant (at 1% level) and negative in binomial probit models (column 3 and 7). We tested whether the relationship is curvilinear by including a square term of component familiarity. Our data do not confirm the curvilinear relationship. In multinomial logit models, the propensity of both plain nonuse and any commercial uses increases as the familiarity with technological components increases. Comparing the coefficients on component familiarity for internal use (column 5) and for external use (column 6), the impact of component familiarity is larger between strategic nonuse and external use than between strategic nonuse and internal use. This supports the bargaining failure argument. On the other hand, the propensity of sleeping patents also increases as technology becomes more familiar, as indicated by the positive and significant coefficient on the component familiarity in column 4. This observation bears an important policy implication. As technology becomes mature and, thus, widely diffused, building patent thickets or fences will be less attractive than commercial use or even plain nonuse. This is because, on one hand, reduced technological uncertainty promotes technology transactions and, on the other hand, protective effectiveness of either a blocking or fencing patent will decrease as the claimable property rights become limited. Conversely, strategic nonuse is more likely to be chosen in emerging technologies. This corroborates the evolutionary explanation of technological advances in which the rents from innovation in the emerging phase of

technology should depend largely on technologically advanced design. Strategic nonuse patents thus play a particularly important rent-protecting role in the design competition before a dominant design appears and competition shifts to price competition.

Table 14.2 Probit and multinomial logistic estimates of determinants of strategic nonuse

	Probit			Multinomial logistic			Probit
		Add patent effectiveness		(reference=strategic nonuse)			
	base	survey measure	CMS measure	sleeping	internal	external	Broad definition
Main variables							
Patent effectiveness (CMS)			0.016**	-0.027*	-0.036**	-0.024	0.012*
			(0.008)	(0.015)	(0.015)	(0.019)	(0.007)
Dummy for missing patent effectiveness			-0.248	0.735**	0.135	0.555	-0.113
			(0.161)	(0.340)	(0.337)	(0.376)	(0.139)
Appropriability of patents		0.266					
		(0.205)					
Capital intensity	0.415	0.390	0.409	0.018	-2.257**	-0.852	0.567*
	(0.324)	(0.325)	(0.329)	(0.647)	(0.952)	(1.008)	(0.307)
Dummy for missing capital intensity	0.050	0.037	0.181	-0.568*	-0.295	-0.042	0.109
	(0.150)	(0.151)	(0.160)	(0.335)	(0.323)	(0.391)	(0.144)
Ln(patent stock)	0.056**	0.057**	0.059**	-0.059	-0.142***	-0.087	0.041*
	(0.024)	(0.023)	(0.024)	(0.049)	(0.047)	(0.064)	(0.022)
Component familiarity	-1.061**	-0.938**	-1.108***	2.075**	1.582*	2.787***	-1.203***
	(0.413)	(0.406)	(0.413)	(0.812)	(0.846)	(0.841)	(0.428)
Controls							
Fragmentation index	-0.056	-0.052	-0.029	0.008	0.067	0.283	0.098
	(0.165)	(0.164)	(0.164)	(0.329)	(0.319)	(0.434)	(0.152)
Large firm	0.250	0.236	0.270	-0.765*	-0.072	-1.218***	0.190
	(0.185)	(0.185)	(0.188)	(0.408)	(0.390)	(0.434)	(0.158)
Inventor in manufacturing unit	-0.156	-0.150	-0.131	-0.270	0.539*	-0.254	-0.115
	(0.164)	(0.164)	(0.167)	(0.391)	(0.320)	(0.450)	(0.151)
Competence-destroying invention	-0.110	-0.111	-0.122	0.424**	0.015	0.456*	0.064
	(0.088)	(0.088)	(0.089)	(0.185)	(0.175)	(0.234)	(0.082)
Complexity of product technology	0.020	0.070	0.030	0.044	-0.037	-0.283	-0.024
	(0.115)	(0.120)	(0.114)	(0.235)	(0.225)	(0.295)	(0.104)
Breadth of openness	0.029*	0.028*	0.031**	-0.051	-0.062**	-0.020	0.013
	(0.016)	(0.016)	(0.016)	(0.032)	(0.031)	(0.039)	(0.015)
Diversity index of collaboration	-0.028	-0.024	-0.030	-0.162	0.140	0.176	-0.078
	(0.055)	(0.056)	(0.056)	(0.128)	(0.117)	(0.132)	(0.054)
Technological value	-0.182***	-0.181***	-0.183***	0.043	0.454***	0.608***	-0.184***
	(0.043)	(0.043)	(0.044)	(0.094)	(0.089)	(0.119)	(0.040)
No immediate demand	0.266***	0.268***	0.283***	-0.273	-0.602***	-0.818***	0.199**
	(0.103)	(0.103)	(0.103)	(0.204)	(0.204)	(0.282)	(0.096)
% Basic R&D (/100)	0.316	0.299	0.268	0.087	-1.382**	-0.438	0.354
	(0.251)	(0.249)	(0.250)	(0.466)	(0.538)	(0.671)	(0.234)

Table 14.2 (continued)

Product invention	-0.176**	-0.170*	-0.297***	0.483**	0.626***	0.348	-0.218**
	(0.089)	(0.089)	(0.107)	(0.216)	(0.212)	(0.259)	(0.095)
Man-month (normalized)	-0.304	-0.296	-0.346	0.812*	0.541	0.734	-0.336*
	(0.222)	(0.223)	(0.226)	(0.465)	(0.460)	(0.557)	(0.203)
Number of inventors	0.006	0.004	0.005	-0.085	0.049	-0.009	-0.028
	(0.024)	(0.024)	(0.024)	(0.052)	(0.044)	(0.063)	(0.023)
Complexity of technology	0.005	0.004	0.005	0.003	-0.011	-0.030	0.006
	(0.013)	(0.013)	(0.013)	(0.027)	(0.025)	(0.031)	(0.012)
Number of citations to the U.S. patents	0.002	0.001	0.001	-0.002	-0.002	-0.004	0.000
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
Number of claims	0.000	0.000	0.000	0.001	-0.003	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.003)
Age of invention	-0.002	-0.002	-0.001	-0.002	0.005	0.013	-0.002
	(0.004)	(0.004)	(0.004)	(0.008)	(0.007)	(0.010)	(0.003)
Semiconductor industry	-0.190	-0.202	-0.164	0.154	0.475	0.235	-0.046
	(0.188)	(0.189)	(0.191)	(0.391)	(0.383)	(0.499)	(0.164)
Electrical engineering	-0.249*	-0.138	-0.174	0.142	0.322	0.566	-0.071
	(0.134)	(0.157)	(0.139)	(0.286)	(0.276)	(0.350)	(0.127)
Chemistry, pharmaceuticals	0.014	0.068	0.024	-0.046	0.054	-0.056	0.072
	(0.152)	(0.154)	(0.150)	(0.301)	(0.299)	(0.372)	(0.137)
Process eng, special equipment	-0.195	-0.105	-0.193	0.195	0.455	0.433	-0.057
	(0.155)	(0.168)	(0.156)	(0.316)	(0.312)	(0.400)	(0.140)
Mechanical eng, machinery	0.033	0.117	0.059	-0.318	0.197	-0.885*	-0.209
	(0.160)	(0.172)	(0.160)	(0.337)	(0.306)	(0.453)	(0.152)
Consumer goods & Construction	0.210	0.244	0.274	-1.963**	0.083	-0.428	-0.096
	(0.270)	(0.270)	(0.275)	(0.876)	(0.497)	(0.670)	(0.265)
Constant	-0.910**	-2.005**	-1.474***	2.341**	1.439	-0.676	-0.815**
	(0.413)	(0.924)	(0.473)	(0.992)	(0.940)	(1.209)	(0.415)
N	1241	1241	1241		1241		1241
Log Likelihood	-533.35	-532.65	-529.75		-1462.90		-669.39
Wald chi2	77.04	77.90	81.98		273.28		76.12
Pseudo R2	0.070	0.071	0.077		0.097		0.061

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

Turning to the control variables, patents with higher technology values are less likely to be used for strategic defensive purpose. Patents without immediate business demands are more likely to be used for strategic defensive purpose. Consistent with conventional wisdom, these effects are relative to commercially used patents rather than to other nonuse patents, as clearly indicated by a significant relationship with uses but no significant relationship with other nonuse in the multinomial regressions.

Interestingly, strategic nonuse patents are more likely to be linked to the existing capabilities of firms than other nonuse patents or externally commercialized patents, as indicated by positive and significant coefficients on competence-destroying invention for sleeping and external patents in the multinomial regressions. A similar pattern is shown for the firm size. The coefficients on large firms are significant and negative for both sleeping and external commercialization in the multinomial regressions. According to these two factors, strategic nonuse and internal commercialization strategy share similarities. Both uses of patents are more favored by large firm and less linked to competence-destroying inventions.

The variables controlling for the strength of patents at patent level do not show significant relationship with the propensity of strategic nonuse. In columns 2 through 7, we additionally controlled for the appropriability regime. In column 2, we control the strength of patent for appropriating innovation constructed from the survey. This variable is aggregated in 30 technology classes. We expect that the higher the strength, the higher the propensity of strategic nonuse because the protective value of patents will be higher.

This variable is positively associated, but not significantly, with the propensity of strategic nonuse. This may be attributed to the measurement error. The variable is constructed from the assessment from the respondents who answered that they used the patents for internal commercialization. This limitation may distort the overall effectiveness of patents for appropriating innovation. Hence, we tested an alternative measure. The patent effectiveness measure provided in the Carnegie Mellon survey (Cohen, Nelson, and Walsh, 2000) was well examined in the literature and showed consistent results. We matched the CMS patent effectiveness measure to the primary industry classification (NAICS). In column 2, it shows significant and positive association with strategic nonuse, as expected. Also, the effects are particularly distinct against sleeping and internally commercialized patents as indicated by the multinomial regressions in columns 4 and 5. This is consistent with conventional wisdom that stronger patents have a larger impact on protective use and uses through contracting.

CHAPTER 15. Conclusion to Part III

This study reveals an empirical reality on the strategic use of patents. In the first part, we reported findings on the strategic use of patents using a recently collected survey to the U.S. inventors. This study shows that a significant portion of U.S. patents are indeed filed for strategic reasons, including blocking, preventing invention-around, player, and fence strategies. We also found that characteristics of technology and firms are significantly associated with different strategies. In particular, confirming findings from Cohen et al., player strategy is favored in complex technologies while fence strategy in discrete technologies. In addition, we found that large firms adopt player strategy more than small and medium firms.

In the second part, we hypothesized that strategic nonuse was driven by several factors related to a firm's financial and technological assets and technology characteristics. As our results indicate, firms are more likely to use a patent for strategic defensive purposes when they have valuable downstream assets. The size of technological assets, as measured by the number of patents owned by a firm, also drives non-practicing strategic patents. The asset protective roles of patents were previously argued by Hall & Zidonis (2001; Ziedonis, 2004). This study is different from their studies in at least two points: first, instead of looking at patent intensity, we directly test the impact of assets on the presence of non-practicing strategic patents compared to other types of use. Second, we

examine the phenomenon across multiple sectors. Third, we showed that, not as well as capital assets, technological assets (patent stock) are also an important determinant of strategic use of patents. This finding is not free from caveats. Strategy of patent use (or nonuse) should depend on management direction of firms and industry dynamics as well as technology characteristics. Future research that incorporates these firm- and industry-specific factors into analysis would advance our understanding on this important phenomenon.

As technology matures and becomes more familiar, the propensity of strategic nonuse decreases because of increased propensity of commercial use. The increased commercial use of mature technology is driven by the nature of innovation (more incremental innovation) but also driven by lowered technological uncertainty. The latter has a greater impact on the external path of commercialization.

CHAPTER 16. Conclusions

16.1. Summary of Findings

In Part I, we examined the effects of evolutionary stages of technology development and firm capabilities on the commercial uses of patented inventions. We found supporting evidence for the arguments that the patented inventions in mature technology are more likely to find a path to commercial applications because of a favorable selection environment of technology and lower uncertainty linked to the general characteristics of mature technology. In addition, the study shows that the impact of component familiarity on commercialization is stronger for complex technologies. We also argued that the patented inventions from capital-intensive firms are less likely to commercialize because of the presence of alternative competitive advantage, progressively increasing organizational rigidity with size, and larger protective value of patents than the benefits from commercialization. Our empirical estimations based on the U.S. inventor survey support these arguments.

In Part II, we examined the impact of technological uncertainty, strong internal complementary assets position, characteristics of knowledge search, and collaboration on the organizational path of commercialization. Based on Teece's framework on the

profitability of innovation, we synthesized various theories to explain why firms choose different organizational paths in the downstream commercialization process. We found that technological uncertainty lowered the friction of market transactions of technology and, hence, favored external paths. The main argument of this hypothesis is borrowed from TCE but also linked to the evolutionary explanation of technological development. Stage of technological development, technological uncertainty, and profitability of innovation are interrelated with each other.

As Teece argued and many following studies showed, a strong internal position for complementary assets have a strong positive impact on the internal commercialization paths. Also, as Tushman and Anderson argued, we found that there was a strong organizational inertia for a firm to tend to keep doing what it had been doing. This implies that firms' development capability would have a strong path dependency and, therefore, may well fall into the competence trap (Levinthal and March, 1993; Levitt and March, 1988).

Departing from Teece, we argue that openness of innovation processes and network relationship should affect the choice of commercialization paths. Consistent with our hypothesis, empirical results show that external knowledge from industrial nature increases the propensity of internal commercialization. Proximity of industrial knowledge to specific industrial problems and a tendency to require more hands-on knowledge typically acquired from field experience would cohere authoritative controls more efficiently than distributed controls across firm boundaries. As hinted by KBV, internal

synergy of this type of technology is expected to be higher. Our analysis also indicates that collaboration has diverging effects on the choice of commercialization paths. While collaboration with firms in vertical relationships tends to favor the internal paths, collaboration with firms in horizontal relationships tends to favor the external paths.

Finally, in Part III, we reported findings on the strategic use of patents and then tested hypotheses about factors driving strategic nonuse. This study shows that a significant portion of U.S. patents are indeed filed for strategic reasons, including blocking, preventing invention-around, player, and fence strategies. We also found that characteristics of technology and firms are significantly associated with different strategies. In particular, confirming findings from Cohen et al., the player strategy is favored in complex technologies, while the fence strategy is favored in discrete technologies. In addition, we found that large firms adopt the player strategy more than small and medium firms. As our regression results indicate, firms are more likely to use a patent for strategic defensive purposes when they have valuable downstream assets. The size of technological assets, as measured by the number of patents owned by a firm, also drives strategic nonuse. As technology matures and becomes more familiar, the propensity of strategic nonuse decreases because of increased propensity of commercial use. The increased commercial use of mature technology is driven by the nature of innovation (more incremental innovation) but also driven by lowered technological uncertainty.

Table 16.1 summarizes the findings.

Table 16.1 Summary of the results

Theory (Key literature)	Measures	Commercial-ization	External commerciali-zation	Strategic nonuse
Assets/ firm size (Schumpeter, Mkt4T, Hall & Ziedonis)	Capital intensity Patent stock	Small Small	Small Not sig	Large Large
Dominant design (Utterback, Dosi) & TCE / Bargaining failure (Merges)	Technology familiarity	+	+	-
Favorable selection environment of mature technologies (Nelson & Winter)	Technology familiarity	?	N/A	N/A
TCE (Mkt4T; Patent strength @ pat level)	Number of different USPC's; Number of claims	Not sig	Not sig	Not sig
Co-specialized assets	Manufacturing unit Competence-enhancing	+ N/A	- -	Not sig Not sig
Open innovation (von Hippel, Chesbrough, Laursen & Salter, KBV)	Importance of external knowledge	Industrial	Public	+
Networks/Alliance (Powell, Uzzi, March, Rothaermel)	Inventive collaboration	+	Horizontal	Not sig

16.2. Contribution to the Field

This study examines the commercialization process of innovation. It shows that the innovation process is determined by multi-level factors at different levels (such as evolutionary stage of technological development at macro level, firm capabilities at organizational level, and various factors at project/invention level) and across organizational boundaries. Also, it casts doubts on the validity of using patents as a proxy for innovativeness. A majority of patented inventions are used for innovation, but a significant portion of them are also used for strategic purposes, which may have some anti-innovative effects. Moreover, our empirical estimations show that a larger patent stock of a firm raises the probability of strategic uses rather than commercial uses. This implies that it would be misleading to measure innovativeness using the number of patents if their actual uses are not properly considered.

This study clearly shows the usefulness of project-level data in understanding innovation. The results from the study are based on a novel and rich data set covering a broad set of covariates at technology, firm, invention, and project levels. We show that invention- and project-level factors are indeed significant determinants of the uses of their outputs. In particular, detailed information on the nature, organizational background, knowledge flows, and the uses of inventions are shown important in understanding innovation. Patent publications also provide this information, but they are in many cases limited or incomplete. Despite their own weaknesses, large-scale surveys on innovation and invention will be a promising vehicle that can lead us to better understanding innovation.

The study has some theoretical implications. It shows that theoretical constructs from the evolutionary explanation of technology development (Abernathy and Clark, 1985; Dosi, 1982; Henderson and Clark, 1990; Utterback, 1994) and Teece's dominant design explanation have some explanatory power in the uses of patented invention and profitability of innovations. In particular, we take a measure of a degree to which a field of technology is populated with patents as a proxy of maturity of a technology field. Furthering the arguments that relate this construct to search the behavior of entities (Fleming, 2001; Fleming and Sorenson, 2001), we proposed a novel explanation how this construct can affect a selection environment of technology adoption. Our estimations, however, do not directly test the validity of this argument because this construct is confounded, both theoretically and empirically, with transaction cost effects. Nevertheless, general characteristics of a mature technology (or post-dominant design stage) such as lower technological uncertainty as suggested by evolutionary economists of technological advance seem to have empirical validity when plugged into a transaction cost explanation.

Previous innovation surveys reported that non-patent appropriability means are heavily utilized by firms (Cohen, Nelson, and Walsh, 2000; Levin et al., 1987). This study suggests that strong ownership of alternative non-patent appropriability means (e.g., higher dependence on capital assets) may direct the inventions (patents) of commercial potential toward hindering the innovation of others. Then stacking of sitting-on or strategic nonuse patents will reinforce the appropriability of non-patent appropriability

means. So appropriability means are not independent from each other but mutually influencing. This observation suggests that the appropriability means may be not only endogenous within a regime of appropriability as claimed by Dosi et al. (2006) but also affected by other appropriability conditions.

By examining the multifaceted aspects of the organizational trajectory of commercializing patented inventions, this study sheds new light on innovation theory, organizational theory, open innovation, and network perspectives of innovation. In particular, building on Teece's framework about strategy for profiting from innovation, it shows that institutional aspects, including social relationship and knowledge exchange, should be regarded as important and independent factors affecting innovation. It also discusses a less-attended element of Teece's framework: dominant design or technological cycle.

First, we confirm that strong internal position for downstream complementary assets favor an internal commercialization strategy. In explaining the relationship between strong coupling with internal complementary assets and vertical integration of downstream commercialization processes, we enriched the discourse by synthesizing theoretical implications from TCE and KBV of a firm. The inventions coming out of strong coupling with firm-specific co-specialized assets will be more bound to the firm-specific assets and retain a higher level of asset specificity between the research and commercialization process. More flavors of firm-specific elements in inventions will lower internal management costs required for coordinating two processes and increase

the costs of switching to external suppliers. This is an explanation based on TCE. KBV emphasizes the prospective aspect. The learning curve advantage and internal coordination attained through the coupling process during the invention process will provide a higher change of internal synergy. Both theories predict the positive relationship between strong internal coupling with complementary assets and vertical integration of downstream commercialization processes. As Conner and Prahalad (1996) claimed, TCE and KBV may explain the same phenomenon from different sides. Considering both theoretical implications will provide a more comprehensive understanding. Apart from the theoretical elaboration to synthesize two complementary theories, this finding contributes to the Teecian framework of profitability of innovation and arguments of markets for technology by providing a direct test of the effects of co-specialized complementary assets on a choice of commercialization paths. One avenue of future research will be looking at how the effects of co-specialized assets on commercialization paths are moderated by the characteristics of technology (e.g., general purpose v. specialized) or by the stage of the technology-development cycle. Our conjecture is that the impact of co-specialized assets on the choice of commercialization paths will be weaker for general-purpose invention or in mature technology.

Second, we confirm that TCE provides valid explanations in the governance structure of downstream assets. While most TCE arguments give attention to make-or-buy decisions, we extended them to integrate-or-sell decisions in an innovation context and provided empirical evidence conforming to theoretical explanation. However, as TCE literature admits, operationalizing TCE constructs is indeed difficult. For example, our

technological uncertainty measure, component familiarity, does not precisely isolate TCE constructs but is confounded with effects from the technological cycle.

Third, this study reveals the importance of an institutional approach in understanding innovation. Furthermore, proceeding one step further from the open innovation arguments, it shows that the nature of external knowledge should be taken into consideration in studying innovation. The previous empirical studies focused on how broadly or deeply firms sourced external knowledge and how they affected intermediate output of the innovation process or firm performance (Katila and Ahuja, 2002; Laursen and Salter, 2006). In doing so, they did not turn their attention to the qualitative differences of sourced knowledge. Other studies examined a limited number of leading firms to show how they had successfully utilized some types of external knowledge for innovation (Dyer and Nobeoka, 2000; von Hippel, 1988). This study attempts to overcome the weaknesses of both studies by examining the impact of different types of external knowledge in a large-scale, cross-industry sample. Furthermore, it reveals not only that the different nature of external knowledge has a different impact on innovation, but also that it would be bound to a different commercialization strategy. While external industrial knowledge is conducive to internal commercialization, external public knowledge spawns external commercialization. Or, the other way around, firms that chose an internal integration strategy would have sought more industrial knowledge, while firms that chose to provide their inventions to external parties for commercialization might have resorted more on public knowledge. Certainly, the analysis leaves more questions open to be answered. Although we tried to justify distinctiveness

between external industrial and public knowledge in the context of mode of commercialization both theoretically and empirically, it still leaves ambiguity in concepts and measurement. First, it overlaps with basic-applied distinction. We argued that they were different because external public sources can deliver an applied type of knowledge, and external industrial sources can deliver basic type of knowledge. We also controlled for the elements of an R&D project. We suggested that, separate from the basic-applied type, technological fitness, learning-curve effects, and inclusions of organizational routines are some discriminating characteristics of this distinction. However, they need to be better articulated in the practical context. Second, external public knowledge is confounded with the maturity of the field of technology as we discussed in Part II. This also contributes to the ambiguity. In summary, further research on the characteristics, drivers, and impact of the different types of knowledge is required.

Fourth, this study shows that collaborative networks, net of knowledge flows, influence the organizational trajectory of commercialization. Furthermore, it shows that relative position of the innovator in the network is indeed an important predictor of the trajectory. By the relative position in the network, we do not mean the structural or topological relations that many studies of networks focus on (Owen-Smith and Powell, 2004) but the relative positions in the value chain or in competitive relations in the product markets. Previous studies argued why particular ties affect the firm or innovation performance (Afuah, 2000; Dyer and Nobeoka, 2000; Gulati and Higgins, 2003; Uzzi, 1996). This study contributes to the field by arguing and showing that firms utilize different types of networks for different innovation strategies. As a novel contribution, it shows that

perspectives on collaborative networks have unique explanatory powers in the region that TCE cannot address. Where technological uncertainty is high, collaboration has a stronger impact on the choice of organizational paths of the downstream process of innovation. This finding empirically corroborates Granovetter's and Powell's (Granovetter, 1985; Powell, 1990) arguments that economic theories alone are incomplete in explaining social behavior so that network perspectives can complement them.

Fifth, the estimations of Part III indicate that firms are more likely to use a patent for strategic defensive purposes when they have valuable downstream assets. The size of technological assets, as measured by the number of patents owned by a firm, also drives non-practicing strategic patents. The asset protective roles of patents were previously argued by Hall and Ziedonis (2001; Ziedonis, 2004). This study is different from their studies in at least two points: first, instead of looking at patent intensity, we directly test the impact of assets on the presence of non-practicing strategic patents compared to other types of use. Second, we examine the phenomenon across multiple sectors. Third, we showed that, not as well as capital assets, technological assets (patent stock) are also an important determinant of strategic use of patents. This finding is not free from caveats. Strategy of patent use (or nonuse) should depend on management direction of firms and industry dynamics as well as technology characteristics. Future research that incorporates these firm- and industry-specific factors into analysis would advance our understanding on this important phenomenon.

16.3. Limitations

This study is not free from limitation. First, uses of patents are identified from the input from one of the inventors. Although the survey is directed to the lead inventor, who we assumed to be better informed than other inventors of uses as well as technological contents of the inventions, some of them may not care about the commercialization process and possibly provided inaccurate answers or responded “don’t know” to the survey. If this is random with regard to our variables of interest, then it will not cause a bias in the estimation. The worst case is that the inventors belonging to an organization in which innovation labor is well distributed across the organization (e.g., large firms) tend to be more ignorant of the downstream processes. Indeed, the proportion of those answering “don’t know” to the use questions are higher for large firms in the survey. Although we showed that this self-selection effect did not result in a significantly biased estimation for our analyses, a better and more accurate measure can be obtained by cross-validating the data by additionally asking R&D or IP managers of firms.

Second, we included a broad set of covariates at technology, firm, invention, and project levels. However, we could not control firm-specific effects. Individual firms may have different commercialization strategies or managerial tendencies. We could not fully control these firm-specific effects because our data set was cross-sectional. Constructing panel data for the uses of patented inventions at the scale of this study will demand huge resources that may not be mobilized by a small group of researchers. However, as national longitudinal surveys in education show, coherent longitudinal surveys on

innovation will substantially advance our understanding of innovation, we believe. Otherwise, a detailed case study for the limited set of firms will populate the gap.

Third, the study does not directly test implications from product market characteristics or industry structure. Instead, it controls broad industry areas and the characteristics of technology fields. Licensing literature argues that some industry and product market aspects, such as the level of competition or the level of product differentiation, should affect the licensing propensity (Arora, 1997). Also, fuller understanding of external commercialization will be possible when we can consider dyadic relationships as well as aspects of financial markets, which we could not address in the study. Although we control some of these effects by including industry dummies, there may still remain some unobserved heterogeneity.

Fourth, the sample of this study is composed of the U.S. patents whose equivalents were also filed in the European Patent Office and the Japanese Patent Office. The additional costs incurred by filing and maintaining patents in multiple jurisdictions affect the sample characteristics in two different ways. First, because small and medium firms are relatively weakly positioned in financial status compared to large firms, they may have been underrepresented in this sampling frame than the sample composed of the patents filed in a single jurisdiction. Second, the additional costs may have the effect of raising the threshold of patenting to sieve out low-quality patents.

Fifth, this study does not address which types of patent uses or nonuses are desirable, or the impact of commercialization on firm performance or economy. We did not examine the amount of private or social benefits attached to each mode of patent use. We presented a survey result about inventors' assessment of economic value of several types of nonuse in Table 13.3 and Table 13.4. However, this analysis is far from a comprehensive analysis from which we can draw a meaningful normative conclusion. The limitations come from weaknesses of measurement and analysis. First, inventors may not be in the best position to assess the economic value of their patented inventions. Indeed, assessing the economic value of a patented invention is not an easy task, especially if the invention is part of a complex product. This is why the controversy about the damage awards for an infringed patent is so sharply divided and equally weighed in the current debate of the patent reform. However, R&D managers or IP managers may be better positioned to know about it. Second, economic value needs to be defined in a more accurate way. Is it private economic value or aggregate social value? One way to assess (minimum) private economic value is to use patent renewal information. Another way is to look at performance in the product markets or stock markets. One type of social value can be captured by tracking how the patented invention contributes to developing future technology. Tracking citations to the focal patent by subsequent patents can be a measure of this type of social value. On top of better measures of value or performance, then we can examine how each mode of use (especially non-practicing strategic patents) affect the private and social value, on one hand, and how they are conditioned on a variety of factors including characteristics and maturity of technology or firm capabilities. This will be a promising avenue for future research.

16.4. Managerial Implications

Some managerial implications on innovation strategy can be derived from this study. Managers in the firms targeting for integrating inventions into their internal production capabilities may need to give attention to the following aspects of the invention process. First, a tight link to firms' existing downstream assets will help. Involving the field engineers working for manufacturing process in the invention process will be one way to do that.

Second, when firms' value chains are disintegrated, collaboration with participants of the value chain such as suppliers or customers will help.

Third, coping with technological developments made by other firms and proactively absorbing them will help in commercializing the inventions. In this sense firms need to bolster competitive intelligence on technological trends of industry. Participating in industry forums/fairs or regular conversation with suppliers over technological issues will work.

For the firms targeting external commercialization paths, the following strategies in the early stage of the innovation process will be worth considering. First, firms should evaluate the general level of demands for the technology and the level of potential users' understanding the technology. Working on mature technology will be a safe choice. Incorporating publicly available knowledge into inventions will be another way.

Second, collaboration with potential users of the technology will be crucial. In particular, firms in horizontal relationships may already have an interest in the technology. Collaboration with them will probably make the invention process more efficient because of aligned goals and shared knowledge and, moreover, foster a trust relationship to make cooperation in the later stage of innovation easier. Especially in emerging technologies, horizontal collaboration will be more effective in commercializing the resultant invention over the networks of firms.

Third, new companies will have to give more attention to public knowledge and such technologies that are not tightly linked to the existing capabilities of the incumbents.

16.5. Policy Implications

The study suggests some policy implications to promote external commercialization of inventions from our findings. First, we show that small firms are more likely than large firms to contribute to enlarging the market for technology.[68] Enlarged markets for technology will bring many benefits to society by enabling knowledge exchange more fluidly across organizations and promoting R&D investment among small firms. Public policy promoting small firm innovations is therefore justified.

---

[68] Recall that our estimation is based on "innovative" firms (see Section 4.1 for discussion of the sample). Accordingly, firms referred here, especially small firms, do not include non-innovative firms.

Second, we found that offering the patented inventions for external parties' commercialization is not as popular in emerging technologies as in mature technologies. To make innovation systems more flexible and efficient, some policy measures that can promote knowledge dissemination in emerging technologies will be desirable.

Third, corporate spin-offs are particularly specialized for competence-destroying innovation. This will be a blood vessel for economic evolution as noted by Schumpeter. To promote corporate spin-offs' public knowledge is particularly important. Any policy to promote public knowledge will be beneficial. Furthermore, public knowledge will also increase the division of innovation labor by promoting the market for technology. Therefore, continuous support of the creation and dissemination of public knowledge will be essential to make the economy more lively and efficient.

The study shows that patent thickets may decelerate as technologies mature. As a field of technology becomes mature and more populated with component technologies, inventions are more likely to be turned into commercial products and less likely to be strategically exploited. This implies that technology evolution may naturally dampen stacking-up of non-practicing strategic patents. On the other hand, emerging technologies will suffer more from stacking non-practicing strategic patents. This is a serious problem because competitions for design play a bigger role in emerging technologies than in mature technologies (Utterback, 1994). It is suggestive of the importance of asymmetric efforts to put the core inventions in emerging technologies in the public domain. Directing public funds and public organizations to conduct more research on emerging

technologies and to put their research results in the public domain (e.g., academic publications) will be one way to do this.

Some implications to patent reforms in the United States can be also derived from this study. The study supports widely accepted beliefs of the importance of higher quality patents in innovation. Our results show that the higher the technological quality of patents, the more likely they will be to commercialize (especially externally) and the less likely be strategically used. The Patent Reform Act of 2009 pending in the United States Senate aims to raise patent quality by enhancing the USPTO examination process, allowing the public to engage in the examination process, expanding the existing *inter partes* reexamination process, and institutionalizing post-grant review procedures. This study does not provide direct answers to the points of technical discussions of the above proposal. However, it suggests that overall direction underlying these proposed changes to enhance the quality of patents is right and promotes innovation.

In Part III, we show that the propensity of strategic exploitation, relative to plain nonuse or internal commercialization, is higher for those patents filed by firms from industries where patent protection is more effective. One element constituting the effectiveness of patent protection is the threat of litigation. The Patent Reform Act of 2009 proposes so-called “apportionment-centric” damage awards, the gist of which is to restrict damage awards accompanying patent infringement to a portion of the total economic value of final products the infringed invention particularly contributes to. According to a survey conducted by Shane (2009), the proposed legislation will lower the damage awards by

about 30 percent. If this reduction results in a decrease of patent effectiveness, then the proposed change will have an effect on reducing strategic nonuse patents according to the empirical estimation of this study. However, the weakened patent effectiveness may also have a negative impact on external use of patents, including licensing as indicated by an insignificant difference in the coefficients on patent effectiveness between strategic nonuse and external use in the estimation of Table 14.2. Indeed, the advocates of the current system argue that reducing damage awards will shrink the market for technology and disincentivize investment in R&D. Total effects can be estimated only if the above two opposing effects are considered together along with the cost of litigation. Although further discussion goes beyond the scope of this study, let us finish this paragraph with one additional thought. Given that the current legal practices are inclined toward awarding "excessive" compensation to the litigants (Thomas, 2007), we doubt if the market for technology will really shrink simply by remedying this excessiveness. Of course, the infringer (or licensee) will be better positioned in litigation (or licensing deals) because of the reduced damage awards (or the reduced level of litigation risks), which, in turn, may make costly R&D investment less attractive to the patent holders. However, if the legal process removes only the excessive portion of compensation (which may be hard to accomplish in practice, especially in complex technologies), then the threat of litigation will be still present and the market for technology will be beneficial to both parties.

If the proposed shift toward an apportionment-centric system of damages results in lowering strategic nonuse patents, the effects will be different between large and small

firms. The study shows that large firms (in terms of employees or capital/technological assets) are more likely than small or medium-sized firms to use patents for strategic purposes and less likely to commercialize them. If the protective (or assaultive) roles of patents decrease as the damage awards lower, the reduction of strategic nonuse patents will mostly come from large firms (or asset-intensive firms). Then, large firms will redirect R&D investment previously put into developing duplicative technologies to other productive activities, including developing innovative technologies. On the other hand, the thinner thickets may form a technological niche that can be exploited by small and medium firms. Certainly, relieving large firms of the burden of maintaining excessive amounts of nonuse patents may make them more efficient and result in strengthening their advantage in technological leadership to stifle small and medium firms. However, this may not necessarily undermine social welfare.

As a way to reduce potential negative effects of non-practicing strategic patents, one may propose a "compulsory licensing" by which the owner of the non-practicing patents possessing a high potential for social benefits is forced to license them to a certain entity, which satisfies a certain condition. The compulsory licensing is deeply rooted in the tradition of intellectual property rights. The Paris Convention for the Protection of Industrial Property (in short, the Paris Convention), effective in 1883 and revised for the last time in 1979, states in Article 5. A (2) that "Each country of the Union shall have the right to take legislative measures providing for the grant of compulsory licenses to prevent the abuses which might result from the exercise of the exclusive rights conferred by the patent, for example, failure to work." In its legal implementation, it has been

applied in a limited and cautious way. In the United States, only the patented inventions funded by the federal government are subject to compulsory licensing. The European Union articulates and restricts both the subject technology (i.e., “pharmaceutical products”) and beneficiaries (i.e., the manufacturer who export to countries with public health problems) in a very cautious way (Regulation (EC) No 816/2006 of the European Parliament and of the Council of 17 May 2006). Suppose that “a certain entity” in the proposal is an innovative small firm and “a certain condition” is commitment and ability to manufacture goods or services based on the licensed technology. For example, imagine a technology protected by a non-practicing patent is assessed to have a potential to enhance social welfare, but the owner of the patent refuses to license it or requires unrealistically high royalties without commercializing it himself. A compulsory licensing scheme then forces the owner to license the patent, at *reasonable* price, to innovative small firms who commit to making a socially beneficial product based on the patented technology and show an ability to complete the development projects. This proposal will have both pro-innovative and anti-innovative effects. Compulsory licensing may reduce patent abuse to promote innovation by putting in use the patents of wider social benefits. Indeed, a recent study by Moser and Voena (2009) shows that compulsory licensing of the foreign patents had a positive impact on domestic invention in the short-term. However, in the long-term, compulsory licensing may lower the value of patents and disincentivize an investment in innovation, which, resultantly, slows down innovation. In addition, expanding compulsory licensing to a wider range of products or territories requires a more cautious approach because of several practical problems. For example, in many cases, determining a threshold level of social benefits beyond which compulsory

licensing is eligible will be disputable. Furthermore, setting a reasonable licensing royalty is not an easy task either. Our analysis suggests that reduction of non-practicing strategic patents may largely come from large firms. However, it also shows that the value (either technological or economic) of non-practicing strategic patents is higher for small firms than for large firms (Table 13.4). Therefore, we cannot conclude whether the proposal will impact more on large firms or small firms based on our analysis. Before implementing this proposal, therefore, further research on both effects and practical issues mentioned above should cumulate.

APPENDIX A. Literature Review

Table A. 1 Summary of empirical studies about licensing

Paper	Category	Thesis/ Findings	Country /industry	Data/ methods
(Arora, 1997)	Determinants of licensing	• Presence of specialized engineering-construction firms => increased licenses => lower entry barrier => induce large incumbents to license more • Licensing : industry structure ○ Presence of competing tech ○ # competing licensers • "licensing is most common in sectors with large scale production facilities, with relatively homogeneous products, and with a large number of new plants. It is less common in sectors marked by product differentiation, custom tailoring of products for customers, and small scales of production."	chemical	• Historical industry case study
(Bessy and Brousseau, 1998)	Determinants of licensing feature	• Horizontal agreements: market sharing; transactional contracts ○ K-commonality: more transactional • Vertical agreements: tech transfer; relational contracts	France 10 large firms	• 10 Case studies • survey
(Anand and Khanna, 2000)	Determinants of licensing feature	• Prominent ind: Chemical, computer, elec • Robust cross-ind diff ○ Incidence of licensing ○ % ex-ante contracts ○ Exclusivity ○ % contracts among those w/ past dyadic relationship ○ # cross-licensing	U.S. Firm level	• Thompson SDC • 1612 Licensing contracts 1990-93 • Verified by Lexis-Nexis => 1365 • Compustat (firm size)
(Gans, Hsu, and Stern, 2002)		• Presence of patents: start-up is more likely to license to an incumbent rather than self-commercializing	USA	• start-up commercialization strategy survey
(Gans and Stern, 2003)	Start-up comm. Vs. lic	• Start-up strategy and interactions with incumbents • "crucial factor determining patterns of competitive interaction between start-up innovators and established firms is the presence or absence of a "market for ideas"" ○ Appropriability (excludability) conditions: type (e.g. patent or secrecy) rather than the level ○ Complementary assets		•

Table A. 1 (continued)

(Fosfuri, 2004)	Determinants of licensing feature	• Licensing tradeoff: "revenue effect" vs. "rent dissipation effect" • % licensing of a chemical firm ○ Quadratic(inverted-U) in # tech suppliers (competing tech) ○ (-) licensor's market share ○ (-) Degree of product differentiation	chemical	• Large chemical firms • 1986-96
(Kollmer and Dowling, 2004)	Determinants of licensing feature	• The importance of licensing decreases with the presence of alternative commercialization channels such as marketing and sales or offered services • presence of marketing and sales activities drives licensing non-core products	USA/ bio	• 70 biopharmaceuti cal firms • OLS, t-test
(Arora and Ceccagnoli, 2006)	Licensing propensity + Patent propensity	• Effectiveness of patent protection : licensing propensity (+) moderated by complementary assets Model: • DV: lic. Prop. & Pat. Prop. • IV: pat. Eff. • CA: R&D & manuf personnel interact daily • Controls: ○ BU size ○ Imp. Of Basic sci ○ Imp of Med sci ○ % R&D in basic sci ○ Tech competition (# rivals) ○ Ind fixed eff • Type org	Firm level	• CMS • 1991-93 • OLS • GMM
(Nagaoka and Kwon, 2006)	x-licensing propensity	• # cross-licensing ○ Patent > only know-how • X-lic/lic. ○ Firm size(empl, pats, R&D)" (+) ○ Symmetric firms: (+)	Japan Manufact	• 1144 lic contracts of 268 firms • Nikkei EEDS • FY 1999
(Kim and Vonortas, 2006)	Determinants of licensing feature	• # license agreements (all and non-exclusive) ○ Current patent stock (+**) ○ Prior license (+**) ○ Patent intensity of industry (+**) ○ Complex industry (-) • # exclusive license ○ Complex industry (-**) • # cross-license ○ Prior license (+**) ○ Complex industry (+**)	U.S. public firms	• 9310 licensing agreements in 90s • Random effects negative binomial estimation

Table A. 1 (continued)

(Gans, Hsu, and Stern, 2007)	Determinants of licensing feature	• Licensing propensity: patent grant (+) • The importance of a patent grant for licensing depends on the strategic environment in which the firm operates o Productivity efficiency effects (tech cycle) o reputation	USA	• 7649 licensing deals in the 90s • Cox proportional hazard rate models
(Gambardella, Giuri, and Luzzi, 2007)	Determinants of licensing	• Willingness to license o Large and medium firm (-) o 4 digit IPC (+) o Knowledge from university (+) • Actual license o Large and medium firm (-)	EU	• PatVal-EU

Table A. 2 Literature about knowledge characteristics and innovation

Author (Year)	Industry	Data/ Technique	Measures of performance	Variable Examined	Effect
Kogut and Zander (2003)	General innovating firms (Sweden)	Pooled cross section/ logit	Knowledge transferred to wholly owned subsidiaries (=1) versus to a third party (licensed or joint ventures)	Codifiability Teachability Complexity (all of these are constructed from multiple survey questions)	-** -** +**
Nerkar and Roberts (2004)	Pharma-ceutical	Longitudinal/ firm-fixed effects	Total sales of a new product in its first full year on the market 1. all products 2. generic 3. novel	# of patents in the same therapeutic area as the new product for the past 10 yrs (proximal tech experience)	+*** + +***
				# of patents in other therapeutic areas for the past 10 yrs (distal tech experience)	- + +
				total product years of market experience in the focal therapeutic area (proximal market experience)	+ +* +
				total product years of market experience in other therapeutic areas (distal market experience)	+*** +*** +***

Table A. 3 Empirical studies on knowledge sources and firm performance

Author (Year)	Industry	Data/ Technique	Measures of performance	Variable Examined	Effect
(Cohen and Levinthal, 1989, 1990)	General	Yale survey, FTC LoB/ Tobit, GLS	Firm R&D intensity	Importance of knowledge from:	
				Users	++***
				Suppliers	-***
				Universities	+***
				Governments	+
(Katila and Ahuja, 2002)	Global robotics industry (JP, US, EU)	Panel /GEE Poisson	Number of new products	Search depth (repetition ratio of citation)	Invert-U**
				Search scope (ratio of new citation)	+*
Caloghirou, Kastelli, and Tsakanikas (2004)	Food and beverage, Chemicals (w/o pharma), radio, television and communication equipment and apparatus, Telecommunication services, Computer and related activities	Cross section/ OLS	the percentage of firms' sales that can be attributed to innovative products or services	Patent databases	-*
				scientific or business journals	+**
				trade fairs and conferences	+
				reverse engineering	+
				the Internet	-/+
Laursen and Salter (2006)	General (U.K.)	Cross section/ tobit	Fraction of firm's innovative products to the world market	Breadth: number of discrete knowledge sources (1-16)	Invert-U***
				Depth: number of discrete knowledge sources that are highly exploited	Invert-U**

Table A. 4 Literature about knowledge sources and the choice of governance mode

Author (Year)	Industry	Data/ Technique	Choice of governance mode	Variable Examined	Effect
Veugelers and Cassiman (1999)	Manufacturing (Belgium)	Cross section: multi-nomial logit	Of upstream innovation resources, 1. make only 2. buy only 3. make and buy	Information from competitors is important	-*** +*** +
				Information from internal sources is important	-* -*** +**
Fontana, Geuna, and Matt (2006)	Food and beverage, Chemicals (w/o pharma), radio, television and communication equipment and apparatus, Telecommunication services, Computer and related activities	Cross section/ negative binomial	Propensity to participate in R&D collaboration with universities or PROs	the mean of the percentage of new products and processes introduced in collaboration with external partners	+
				scientific and business journals	+**
Gambardella, Giuri, and Luzzi (2007)	Cross-industry	Pooled cross-section/ Probit (selection)	Willingness to license	Knowledge from public research organization	+***
			Actual license		+***

APPENDIX B. Data Appendix for Part I

Table A. 5 Correlation matrix for Part I (N=1239)

1	Any commercialization	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2	Component familiarity	0.00	1.00																	
3	Capital intensity	-0.14*	-0.01	1.00																
4	Dummy for missing capital intensity	0.15*	-0.03*	-0.37*	1.00															
5	Large firm	-0.10*	-0.04*	0.22*	-0.55*	1.00														
6	Ln(patent stock)	-0.18*	0.01	0.28*	-0.67*	0.59*	1.00													
7	Inventor in manufacturing unit	0.10*	-0.06*	-0.03*	0.08*	-0.07*	-0.10*	1.00												
8	Industrial knowledge	0.14*	-0.07*	-0.05*	0.09*	-0.06*	-0.13*	0.05*	1.00											
9	Public knowledge	-0.06*	0.11*	-0.02*	0.03*	-0.07*	-0.05*	-0.05*	0.42*	1.00										
10	Dummy for collaboration	0.11*	-0.03*	-0.05*	0.13*	-0.09*	-0.17*	-0.01	0.22*	0.14*	1.00									
11	Technological value	0.22*	0.00	-0.05*	0.12*	-0.14*	-0.16*	0.02	0.15*	0.21*	0.11*	1.00								
12	No immediate demand	-0.09*	0.06*	0.01	-0.01	0.01	0.04*	-0.04*	-0.04*	0.09*	0.00	0.07*	1.00							
13	% Basic R&D (/100)	-0.09*	0.10*	0.01	0.00	0.00	0.02	-0.04*	0.05*	0.24*	0.02	0.11*	0.12*	1.00						
14	Product invention	0.05*	-0.04*	-0.12*	0.00	0.01	0.00	0.01	0.03*	-0.04*	-0.04*	-0.06*	-0.04*	-0.10*	1.00					
15	Man-month	0.05*	0.01	0.03*	0.03*	-0.04*	0.00	-0.04*	0.14*	0.25*	0.11*	0.20*	-0.03*	0.06*	-0.08*	1.00				
16	Number of inventors	0.06*	0.04*	0.08*	-0.05*	0.04*	0.09*	-0.06*	0.07*	0.06*	0.02*	0.08*	-0.03*	0.02*	-0.05*	0.27*	1.00			
17	Complexity of technology	-0.03*	0.02*	0.13*	-0.02	0.02*	0.00	-0.04*	0.04*	0.05*	0.00	0.08*	-0.02*	0.01	-0.10*	0.04*	0.02*	1.00		
18	Number of claims	0.00	-0.06*	-0.04*	0.07*	-0.10*	-0.10*	-0.04*	-0.03*	-0.04*	-0.01	0.06*	-0.01	-0.04*	-0.01	0.01	0.09*	0.08*	1.00	
19	Age of invention	0.04*	-0.01	-0.04*	-0.06*	0.04*	0.05*	0.06*	0.04*	0.04*	0.01	-0.06*	-0.03*	-0.04*	0.01	0.01	-0.01	0.02*	-0.06*	1.00
20	Electrical engineering	0.00	0.07*	-0.09*	-0.06*	0.01	0.09*	-0.06*	-0.08*	0.03*	-0.08*	-0.04*	0.04*	-0.01	0.03*	-0.12*	-0.12*	-0.08*	0.00	0.08*
21	Instruments	-0.03*	-0.03*	-0.08*	-0.04*	-0.04*	-0.01	-0.05*	0.03*	0.04*	0.01	-0.02*	-0.01	-0.05*	0.04*	0.02*	0.07*	-0.12*	0.07*	0.04*
22	Chemistry, pharma	-0.05*	0.14*	0.20*	0.04*	0.01	-0.02*	-0.07*	0.04*	0.15*	-0.01	0.08*	-0.01	0.15*	-0.10*	0.17*	0.11*	0.26*	-0.03*	-0.07*
23	Process eng	0.02*	-0.07*	0.02*	-0.01	0.02*	-0.02*	0.06*	0.02	-0.10*	0.01	0.00	-0.03*	-0.01	-0.12*	0.00	0.02*	0.05*	-0.03*	-0.02
24	Mechanical eng, machinery	0.03*	-0.13*	-0.04*	0.02*	0.03*	-0.02	0.14*	-0.05*	-0.14*	0.06*	-0.03*	0.03*	-0.08*	0.11*	-0.09*	-0.08*	-0.11*	-0.04*	-0.04*
25	Consumer & Construction	0.07*	-0.06*	-0.06*	0.11*	-0.09*	-0.09*	0.06*	0.10*	-0.06*	0.05*	0.02	-0.07*	-0.03*	0.09*	0.01	-0.01	-0.02*	0.05*	-0.01

* denotes 5% significance level

APPENDIX C. Data Appendix for Part II

Table A. 6 Correlation matrix for Part II (restricted sample, N=651)

1	Internal commercialization	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
2	Inventor in manufacturing unit	0.09*	1.00																			
3	Competence-destroying invention	-0.11*	-0.01	1.00																		
4	Component familiarity	-0.12*	-0.06*	0.02	1.00																	
5	Interaction (4*9)	-0.10*	-0.04*	0.05*	0.06*	1.00																
6	Industrial knowledge	0.03*	0.02	0.11*	-0.05*	0.06*	1.00															
7	Public knowledge	-0.18*	-0.06*	0.13*	0.11*	0.07*	0.47*	1.00														
8	Collaboration - vertical	0.05*	0.01	0.09*	-0.08*	0.15*	0.28*	0.09*	1.00													
9	Collaboration - horizontal	-0.11*	-0.04*	0.07*	-0.04*	0.71*	0.10*	0.09*	0.21*	1.00												
10	Collaboration - public	-0.10*	-0.02	0.05*	0.04*	0.08*	0.15*	0.38*	0.13*	0.13*	1.00											
11	Large firm	0.23*	-0.10*	-0.04*	-0.04*	0.02	-0.01	-0.07*	-0.02	0.02	-0.15*	1.00										
12	Ln(patent stock)	0.12*	-0.11*	-0.04*	0.01	-0.03*	-0.11*	-0.05*	-0.14*	-0.06*	-0.12*	0.58*	1.00									
13	Technological value	-0.13*	-0.01	0.12*	-0.01	-0.02	0.11*	0.18*	0.05*	0.00	0.08*	-0.12*	-0.13*	1.00								
14	No immediate demand	0.01	-0.04*	-0.06*	0.01	-0.03*	-0.01	0.10*	0.03*	-0.02	-0.02	-0.01	0.02	0.10*	1.00							
15	% Basic R&D (/100)	-0.08*	-0.05*	0.11*	0.04*	0.02	0.11*	0.26*	0.01	0.07*	0.14*	-0.01	0.02	0.13*	0.11*	1.00						
16	Product invention	0.07*	0.01	-0.05*	-0.04*	-0.03*	0.07*	-0.04*	-0.03	-0.03*	0.01	0.02	0.02	-0.08*	-0.03*	-0.08*	1.00					
17	Man-month	-0.08*	-0.04*	0.12*	-0.02	0.02	0.15*	0.22*	0.07*	0.06*	0.07*	-0.02	0.04*	0.15*	0.00	0.07*	-0.07*	1.00				
18	Number of inventors	0.01	-0.07*	0.02	0.02	0.00	0.06*	0.04*	-0.05*	0.02	-0.02	0.05*	0.10*	0.05*	-0.02	0.02	-0.04*	0.29*	1.00			
19	Complexity of technology	-0.02	-0.08*	0.02	0.06*	-0.05*	0.05*	0.10*	0.02	-0.06*	0.05*	0.01	-0.05*	0.12*	0.00	0.10*	-0.09*	0.01	-0.03	1.00		
20	Number of claims	-0.05*	-0.05*	0.04*	-0.04*	-0.02	-0.01	-0.07*	0.00	0.01	0.03	-0.11*	-0.14*	0.11*	-0.03*	-0.02	-0.05*	0.02	0.10*	0.07*	1.00	
21	Age of invention	-0.01	0.07*	0.02	-0.02	-0.04*	0.09*	0.12*	0.00	-0.05*	0.02	0.10*	0.13*	-0.07*	0.00	0.01	-0.03	0.02	0.00	0.05*	-0.10*	1.00
22	Electrical engineering	-0.04*	-0.06*	0.05*	0.10*	0.00	-0.09*	0.01	-0.09*	-0.02	-0.04*	0.05*	0.14*	-0.01	0.05*	0.03*	0.03	-0.06*	-0.08*	-0.06*	-0.01	0.08*
23	Instruments	-0.02	-0.02	-0.07*	-0.03*	-0.01	0.03*	0.09*	0.03*	-0.02	0.03*	-0.06*	-0.03*	0.00	0.00	-0.05*	0.02	0.07*	0.14*	-0.14*	0.03*	0.00
24	Chemistry, pharmaceuticals	-0.06*	-0.08*	0.02	0.14*	0.03*	0.07*	0.17*	-0.04*	-0.01	0.09*	0.03	-0.05*	0.04*	0.00	0.15*	-0.11*	0.09*	0.05*	0.26*	-0.03*	-0.04*
25	Process eng, special equipment	-0.01	0.02	-0.03	-0.08*	0.01	-0.01	-0.15*	0.04*	0.05*	-0.04*	0.03	-0.01	-0.02	-0.04*	-0.02	-0.10*	-0.06*	-0.01	0.06*	-0.01	-0.02
26	Mechanical eng, machinery	0.14*	0.14*	-0.01	-0.15*	-0.04*	-0.03*	-0.14*	0.08*	-0.02	-0.06*	0.01	-0.02	-0.01	0.02	-0.11*	0.11*	-0.06*	-0.10*	-0.13*	0.00	-0.04*
27	Consumer goods & Construction	0.01	0.06*	0.04*	-0.07*	0.00	0.08*	-0.05*	0.02	0.06*	0.01	-0.10*	-0.09*	0.02	-0.08*	-0.04*	0.12*	0.02	-0.02	-0.02	0.05*	0.00

* denotes 5% significance level

APPENDIX D. Factor Analysis of Knowledge Sources

In order to extract latent factors underlying knowledge sources, we conduct a factor analysis. First, GT/RIETI survey asks inventors to rate how important each source of knowledge for 1) suggesting and 2) completing the research that led to the patented invention, separately. We provides 12 categories of knowledge sources with 6-point Likert-scale (0: "Did not use", 1: "Not Important" and 5: "Very Important"). The sources of knowledge shown in the survey are: "Scientific and technical literature," "Patent literature," "Fair or exhibition," "Technical conferences and workshops," "Standard documents (for example ISO standards or contributions)," "Your firm, excluding co-inventors," "Universities," "Government research organizations," "Customers or product users," "Suppliers," "Competitors (for example, by reverse engineering)," and "Other relevant sources (please specify)." Because our research hypotheses are only relevant to external sources of knowledge we do not include "Your firm, excluding co-inventors" in our factor analysis. Also, we examine answers in "Other relevant sources" and reassigned some of them to the closest of the above-listed categories. The remaining observations in "Other relevant sources", whose number is ignorable, are not included in the factor analysis to reduce complexity in interpretation.[69] In addition, we further restrict the sample to those patented inventions whose inventor belongs to firms (N=1740).

To test the goodness-of-fit of the latent factor structure, we conduct a confirmatory factor analysis. We use SAS CALIS procedure. The Goodness-of-fit (GFI) index is 0.9965, Bentler's Comparative Fit Index (CFI) 0.9979, McDonald's Centrality Index (MCI) 0.9980, Bentler & Bonnet's Non-Normed Index(NNI) 0.9958, Bentler & Bonnet's NFI 0.9914, root mean square of residual (RMR) 0.0140, and root mean squared error of approximation (RMSEA) 0.0136. All these statistics well exceed the rule-of-thumb cut-off criteria (0.95 for GFI and CFI; 0.90 for MCI; lower than 0.08 for RMR; lower than 0.06 for RMSEA)(Hu and Bentler, 1999). The likelihood ratio chi-square statistic is 28.79 for 22 degrees of freedom with probability 0.1511. This implies that the difference

[69] We also conducted a factor analysis including "Your firm." This item is grouped with "industry sources" and does not make much difference in the structure of latent factors.

between the observed and expected matrices is not significant. Therefore, we confirm the underlying factor structure as hypothesized. The reliability of measures for each factor as calculated by Cronbach's α (rightmost column) is close to Nunally's criterion of 0.7 (Nunnally, 1978). The standardized factor scores and Cronbach's α are summarized in Table 13.

Table A. 7 Standardized regression factor scores

Sources of external knowledge (manifest variables)	Common factors: Industrial knowledge	Common factors: Public knowledge	Cronbach Coefficient Alpha (standardized)
Patent literature	0.1317	0.0115	0.6772
Fair or exhibition	0.3623	0.0579	
Standard documents	0.2018	0.0880	
Customers or product users	0.1398	0.0690	
Suppliers	0.1259	0.0524	
Competitors	0.1244	0.0657	
Scientific and technical literature	0.0248	0.1216	0.7138
Technical conferences and workshops	0.0598	0.3813	
Universities	0.0860	0.1744	
Government research organizations	0.1094	0.2750	

APPENDIX E. Data Appendix for Part III

Table A. 8 Technology characteristics and patenting strategy by 30 subgroups of technology

	Characteristics of Technology				Patenting Strategy		
Technological Area	Complexity of product technology	Importance of complementary technology	Importance of patents	Importance of short lead-time	Cross-licensing	Player strategy	Fence Strategy
Audiovisual	Hi	Hi	Low	Hi	52.8	28.9	15.4
IT	Hi	Hi	Low	Low	47.4	24.7	23.7
Optical	Hi	Low	Hi	Low	44.1	22.6	18.8
Matprocessing/Textile	Low	Low	Low	Low	23.0	19.7	33.3
Telecom	Hi	Low	Low	Low	44.0	19.0	14.7
Semiconductors	Hi	Hi	Hi	Hi	41.1	16.1	16.1
Motors	Low	Low	Low	Low	15.6	14.1	28.1
Handl/Printing	Hi	Low	Low	Low	18.6	14.0	34.9
Electr/Energy	Hi	Low	Hi	Hi	22.8	13.9	42.0
ChemEngineering	Hi	Low	Low	Hi	15.4	13.5	28.9
Pharmaceuticals/ Cosmetics	Low	Hi	Low	Hi	26.1	13.3	40.0
Analysis/Measurement	Hi	Low	Hi	Low	25.0	12.5	34.7
Materials	Low	Low	Hi	Low	24.5	11.5	41.2
NuclearTechn	Hi	Low	Low	Low	22.2	11.1	22.2
SurfaceTechn	Low	Hi	Low	Hi	11.5	9.6	39.2
Agric&Food Process-Mac	Low	Hi	Hi	Hi	18.2	9.1	45.5
OrganicChem	Hi	Hi	Hi	Low	19.6	8.8	23.1
Polymers	Low	Hi	Hi	Hi	17.3	8.6	32.1
Transportation	Low	Hi	Hi	Hi	10.4	8.3	37.5
ConstrTechn	Low	Low	Hi	Hi	8.3	8.3	41.7
PetrolChem/materialsC	Low	Low	Hi	Hi	15.8	7.9	21.1
MedicalTechn	Low	Hi	Hi	Low	14.0	7.8	36.2
Environment	Low	Hi	Hi	Hi	20.0	6.7	40.0
Biotechnology	Hi	Hi	Low	Hi	18.8	6.3	25.0
MachineTools	Hi	Low	Hi	Low	7.0	4.7	27.9
ConsGoods	Hi	Hi	Low	Hi	3.2	3.2	43.3
MechElements	Low	Low	Low	Low	7.8	2.0	37.3
SpaceTech/Weapons	Hi	Hi	Hi	Low	0.0	0.0	20.0
ThermProcesses	Low	Low	Low	Low	0.0	0.0	33.3
Agric&Foods	Low	Hi	Low	Hi	13.3	0.0	46.7
Total					24.5	13.3	30.2

Table A. 9 Share of patents giving a high importance to the reasons of patenting by the size of firms and by industry

Reasons to patent	firm size	EE	Inst	Chem & Pharm	Process	Mech	Cons & Const	All
Commercial exploitation	Small & medium	83.9%	91.3%	87.3%	92.3%	93.3%	90.9%	89.1%
	Large	74.1%	77.9%	89.3%	81.5%	83.0%	80.6%	80.8%
Blocking (offensive)	Small & medium	43.4%	50.7%	43.4%	42.3%	44.8%	36.4%	45.2%
	Large	44.4%	46.8%	45.3%	55.4%	42.2%	48.3%	46.4%
Pure defense	Small & medium	48.1%	34.3%	45.3%	46.2%	39.3%	27.3%	41.4%
	Large	46.5%	51.2%	40.7%	48.7%	41.1%	41.4%	45.6%
Fence strategy	Small & medium	30.9%	28.8%	25.9%	34.6%	40.0%	27.3%	30.6%
	Large	24.3%	40.8%	39.4%	40.5%	40.5%	60.7%	36.5%
Firm's reputation	Small & medium	36.4%	31.8%	46.4%	50.0%	26.7%	36.4%	37.7%
	Large	36.4%	31.8%	23.1%	25.4%	24.9%	20.7%	28.9%
Licensing	Small & medium	40.0%	33.8%	50.0%	50.0%	43.3%	54.5%	42.7%
	Large	36.4%	22.4%	27.1%	26.7%	18.4%	3.6%	26.9%
Cross-licensing (negotiation)	Small & medium	13.2%	21.2%	28.3%	8.0%	3.4%	9.1%	16.9%
	Large	45.8%	27.6%	17.7%	20.9%	11.4%	3.4%	26.4%
Preventing inventing-around	Small & medium	22.6%	18.5%	28.8%	26.9%	17.2%	18.2%	22.5%
	Large	17.3%	24.3%	20.8%	29.2%	15.1%	31.0%	21.2%
Player strategy	Small & medium	11.3%	18.2%	20.8%	4.0%	3.4%	9.1%	13.5%
	Large	30.1%	18.2%	11.4%	17.3%	9.2%	3.4%	18.1%
Inventor's reputation	Small & medium	16.7%	13.6%	13.2%	20.0%	13.8%	9.1%	14.7%
	Large	18.8%	16.0%	13.9%	9.9%	11.7%	6.9%	14.6%

Table A. 10 Correlation matrix for Part III (N=1241)

1	Strategic nonuse (narrow)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
2	Strategic nonuse (broad)	0.77*	1.00																									
3	Patent effectiveness (CMS)	0.03*	0.01	1.00																								
4	Missing patent effectiveness	-0.07*	-0.06*	0.00	1.00																							
5	Appropriability of patents	0.08*	0.06*	0.11*	-0.01	1.00																						
6	Capital intensity	0.09*	0.11*	-0.02*	-0.21*	0.05*	1.00																					
7	Missing capital intensity	-0.07*	-0.07*	-0.02*	0.64*	0.10*	-0.35*	1.00																				
8	Ln(patent stock)	0.13*	0.12*	-0.07*	-0.46*	-0.09*	0.24*	-0.68*	1.00																			
9	Component familiarity	-0.04*	-0.05*	0.11*	-0.01	-0.20*	-0.01	-0.05*	0.01	1.00																		
10	Fragmentation index	-0.02*	-0.03*	-0.01	0.10*	-0.01	-0.10*	0.11*	-0.15*	-0.04*	1.00																	
11	Large firm	0.10*	0.10*	-0.06*	-0.42*	-0.02*	0.22*	-0.57*	0.60*	-0.05*	-0.06*	1.00																
12	Manufacturing unit	-0.02*	-0.04*	-0.06*	0.04*	0.00	-0.05*	0.08*	-0.09*	-0.05*	-0.01	-0.06*	1.00															
13	Competence-destroying	-0.06*	-0.01	0.07*	0.04*	0.00	-0.04*	0.06*	-0.05*	0.02*	0.01	-0.04*	-0.03*	1.00														
14	Complexity of product	-0.02*	-0.01	-0.13*	-0.02*	-0.45*	-0.02*	-0.13*	0.14*	0.12*	-0.01	0.05*	-0.05*	-0.02*	1.00													
15	Breadth of openness	0.01	0.00	0.02*	0.01	0.10*	-0.03*	0.05*	-0.06*	0.03*	0.06*	-0.04*	0.01	0.07*	-0.05*	1.00												
16	Collaboration diversity	-0.03*	-0.06*	0.05*	0.03*	0.04*	-0.03*	0.07*	-0.11*	-0.04*	0.03*	-0.04*	0.01	0.03*	-0.08*	0.20*	1.00											
17	Technological value	-0.13*	-0.15*	0.05*	0.14*	0.04*	-0.05*	0.13*	-0.17*	-0.01	0.02*	-0.15*	0.03*	0.14*	-0.07*	0.15*	0.09*	1.00										
18	No immediate demand	0.05*	0.05*	-0.07*	0.00	-0.04*	0.03*	-0.02*	0.06*	0.04*	0.00	0.04*	0.00	-0.04*	0.03*	-0.01	0.01	0.06*	1.00									
19	% Basic R&D	0.05*	0.07*	0.07*	0.01	-0.01	0.01	-0.01	0.02*	0.10*	-0.07*	0.01	-0.05*	0.10*	0.05*	0.11*	0.03*	0.10*	0.05*	1.00								
20	Product invention	-0.04*	-0.05*	0.44*	-0.02*	0.00	-0.11*	-0.01	0.01	-0.02*	0.03*	0.02	0.00	0.02*	-0.07*	0.02*	-0.01	-0.06*	-0.08*	-0.07*	1.00							
21	Man-month	-0.02*	-0.04*	0.10*	-0.03*	0.05*	0.02*	0.02*	0.00	0.01	-0.04*	-0.02*	-0.04*	0.14*	-0.05*	0.20*	0.10*	0.17*	-0.03*	0.06*	-0.06*	1.00						
22	Number of inventors	0.02*	0.00	0.08*	-0.06*	0.08*	0.05*	-0.07*	0.08*	0.05*	0.00	0.05*	-0.07*	0.05*	0.01	0.10*	0.00	0.08*	-0.03*	0.01	-0.04*	0.27*	1.00					
23	# USPC	0.03*	0.05*	0.01	0.00	0.05*	0.09*	-0.01	0.01	0.01	0.01	0.03*	-0.06*	0.04*	-0.12*	0.06*	0.00	0.09*	0.02	0.05*	-0.09*	0.04*	0.05*	1.00				
24	# backward citations	0.01	-0.01	0.07*	0.03*	0.12*	-0.04*	0.07*	-0.09*	-0.03*	0.37*	-0.03*	-0.02	0.08*	-0.11*	0.03*	0.01	0.03*	-0.03*	-0.02*	-0.01	0.02*	0.11*	0.04*	1.00			
25	Number of claims	0.01	0.01	0.02*	0.11*	-0.02*	-0.05*	0.09*	-0.10*	0.05*	0.13*	-0.12*	-0.04*	0.01	0.03*	0.00	-0.01	0.05*	0.00	-0.03*	-0.04*	0.04*	0.08*	0.07*	0.14*	1.00		
26	Age of invention	0.00	-0.01	-0.03*	0.01	-0.05*	-0.02*	-0.06*	0.05*	0.02*	0.01	0.04*	0.05*	-0.01	0.02*	0.01	-0.01	-0.04*	-0.01	-0.03*	0.01	0.00	-0.01	0.02*	0.01	-0.04*	1.00	
27	Semiconductor industry	-0.04*	-0.02*	-0.18*	-0.14*	-0.12*	0.06*	-0.16*	0.08*	0.03*	0.01	0.09*	-0.03*	-0.03*	0.20*	-0.02*	-0.04*	-0.06*	0.06*	-0.03*	0.01	-0.10*	-0.04*	-0.01	-0.08*	-0.02	0.05*	1.00
28	Electrical engineering	-0.07*	-0.03*	-0.23*	0.01	-0.54*	-0.08*	-0.09*	0.12*	0.04*	0.08*	0.03*	-0.05*	-0.01	0.49*	-0.05*	-0.07*	-0.05*	0.06*	-0.01	0.02*	-0.11*	-0.09*	-0.06*	-0.09*	-0.01	0.08*	0.27*
29	Chemistry, pharma	0.04*	0.04*	0.13*	-0.03*	0.18*	0.19*	0.03*	-0.03*	0.16*	-0.21*	0.00	-0.06*	0.10*	-0.36*	0.10*	-0.03*	0.07*	-0.01	0.14*	-0.07*	0.18*	0.11*	0.24*	-0.04*	0.00	-0.06*	-0.13*
30	Process eng.	-0.01	0.02*	0.00	-0.03*	-0.10*	0.04*	0.00	-0.02*	-0.07*	0.03*	0.03*	0.06*	-0.02*	0.03*	-0.03*	0.03*	-0.01	-0.05*	-0.01	-0.09*	0.00	0.02*	0.05*	0.02*	-0.03*	-0.02*	-0.10*
31	Mechanical eng,	0.01	-0.04*	0.00	0.02	0.02*	-0.04*	0.06*	-0.05*	-0.12*	0.03*	0.01	0.12*	-0.04*	-0.28*	-0.09*	0.04*	-0.01	0.03*	-0.08*	0.10*	-0.10*	-0.10*	-0.11*	-0.01	-0.04*	-0.03*	-0.08*
32	Consumer & Construction	0.01	-0.03*	0.01	0.11*	0.07*	-0.05*	0.10*	-0.09*	-0.05*	0.07*	-0.07*	0.04*	0.02*	0.04*	0.03*	0.03*	0.02*	-0.07*	-0.03*	0.08*	0.02*	0.00	-0.03*	0.08*	0.03*	-0.01	-0.05*

* $p<0.05$

REFERENCES

Abernathy, W. J., and James M. Utterback. 1978. Patterns of Industrial Innovation. *Technology Review* 80 (7):40.

Abernathy, William J., and Kim B. Clark. 1985. Innovation: Mapping the winds of creative destruction. *Research Policy* 14 (1):3-22.

Abrahamson, Eric. 1991. Managerial Fads and Fashions: The Diffusion and Rejection of Innovations. *Academy of Management Review* 16 (3):586-612.

Acs, Zoltan J. 2002. *Innovation and the Growth of Cities*. Northampton, MA: Edward Elgar Publishing, Inc.

Acs, Zoltan J., and David B. Audretsch. 1987. Innovation, Market Structure, and Firm Size. *Review of Economics & Statistics* 69 (4):567.

———. 1988. Innovation in Large and Small Firms: An Empirical Analysis. *American Economic Review* 78 (4):678.

Afuah, Alan. 2003. *Innovation Management: Strategies, Implementation and Profits*: Oxford University Press.

Afuah, Allan. 2000. How much do your co-opetitors' capabilities matter in the face of technological change? *Strategic Management Journal* 21 (3):397-404.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. Competition and Innovation: An Inverted-U Relationship. *Quarterly Journal of Economics* 120 (2):701-728.

Ai, Chunrong, and Edward C. Norton. 2003. I nteraction terms in logit and probit models. *Economics Letters* 80:123-129.

Alcacer, Juan, Michelle Gittelman, and Bhaven Sampat. 2009. Applicant and examiner citations in U.S. patents: An overview and analysis. *Research Policy* 38 (2):415-427.

Anand, Bharat N., and Tarun Khanna. 2000. The Structure of Licensing Contracts. *Journal of Industrial Economics* 48 (1):103-135.

Anderson, Philip, and Michael L. Tushman. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly* 35 (4):604-633.

Arora, Ashish. 1997. Patents, licensing, and market structure in the chemical industry. *Research Policy* 26 (4-5):391-403.

Arora, Ashish, and Marco Ceccagnoli. 2006. Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing. *Management Science* 52 (2):293-308.

Arora, Ashish, and Andrea Fosfuri. 2003. Licensing the market for technology. *Journal of Economic Behavior & Organization* 52 (2):277-295.

Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella. 2002. *Markets for Technology: The Economics of Innovation and Corporate Strategy*. Cambridge, MA: MIT Press.

Arrow, Kenneth J. 1969. The Organization of Economic Activity: Issues Pertinent to the Choice of Market versus Non-market Allocation. In *The Analysis and Evaluation of Public Expenditure: The PPB System*. Washington, DC: Joint Economic Committee, 91st Congress, 1st Session.

Arthur, W. Brian. 1990. Positive Feedbacks in the Economy. *Scientific American* 262:92-99.

Arundel, Anthony. 2001. The relative effectiveness of patents and secrecy for appropriation. *Research Policy* 30 (4):611-624.

Barney, Jay B. 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management* 17 (1):99-120.

Baumol, William J. 2002. *The Free-Market Innovation Machine*. Princeton, NJ: Princeton University Press.

Bessy, Christian, and Eric Brousseau. 1998. Technology licensing contracts features and diversity. *International Review of Law and Economics* 18 (4):451-489.

Blind, Knut, Jakob Edler, Rainer Frietsch, and Ulrich Schmoch. 2006. Motives to patent: Empirical evidence from Germany. *Research Policy* 35 (5):655-672.

Blundell, Richard, Rachel Griffiths, and John Van Reenen. 1999. Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *Review of Economic Studies* 66 (3):529-554.

Business Wire. 2003. Samsung Electronics Announces 7th Generation TFT-LCD Glass substrate. *Business Wire*, June 3.

Caloghirou, Yannis, Ioanna Kastelli, and Aggelos Tsakanikas. 2004. Internal capabilities and external knowledge sources: complements or substitutes for innovative performance? *Technovation* 24 (1):29-39.

Cantwell, John. 2005. Innovation and Competitiveness. In *The Oxford Handbook of Innovation*, edited by J. Fagerberg, D. C. Mowery and R. R. Nelson. Oxford, UK: Oxford University Press.

Carlile, Paul R. 2002. A Pragmatic View of Knowledge and Boundaries: Boundary Objects in New Product Development. *Organization Science* 13 (4):442-455.

Ceccagnoli, Marco. 2009. Appropriability, Preemption, and Firm Performance. *Strategic Management Journal* 30:81-98.

Chandy, Rajesh K., and Gerard J. Tellis. 1998. Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize. *Journal of Marketing Research* 35:474-487.

Chesbrough, Henry W. 2003. *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston, Massachusetts: Harvard Business School Press.

Chesbrough, Henry W., and Melissa M. Appleyard. 2007. Open Innovation and Strategy. *California Management Review* 50 (1):57-76.

Christensen, Clayton M. 2003. *The Innovator's Dilemma*: Collins Business.

Coase, Ronald H. 1937. The Nature of the Firm. *Economica* 4 (16):386-405.

Cohen, Jacob, Patricia Cohen, Stephen G. West, and Leona S. Aiken. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*. 3rd ed. Mahwah, NJ: Lawrence Erlbaum Associates.

Cohen, Wesley M., Akira Goto, Akiya Nagata, Richard R. Nelson, and John P. Walsh. 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research Policy* 31 (8-9):1349-1367.

Cohen, Wesley M., and Steven Klepper. 1996a. Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D. *Review of Economics & Statistics* 78 (2):232.

———. 1996b. A Reprise of Size and R & D. *Economic Journal* 106 (437):925-951.

Cohen, Wesley M., and Daniel A. Levinthal. 1989. Innovation and Learning: The Two Faces of R & D. *Economic Journal* 99 (397):569-596.

———. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35:128-152.

Cohen, Wesley M., Richard R. Nelson, and John P. Walsh. 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not): NBER.

———. 2002. Links and Impacts: The Influence of Public Research on Industrial R&D. *Management Science* 48 (1):1-23.

Conner, Kathleen R., and C. K. Prahalad. 1996. A Resource-based Theory of the Firm: Knowledge Versus Opportunism. *Organization Science* 7 (5):477-501.

Criscuolo, Paola. 2006. The 'home advantage' effect and patent families. A comparison of OECD triadic patents, the USPTO and the EPO. *Scientometrics* 66 (1):23-41.

Cushing, Christiadi, and Brian Cushing. 2007. Conditional Logit, IIA, and Alternatives for Estimating Models of Interstate Migration. In *46th annual meeting of the Southern Regional Science Association*. Charleston, SC.

David, Paul A. 1985. Clio and the Economics of QWERTY. *American Economic Review* 75 (2):332.

Dosi, Giovanni. 1982. Technological paradigms and technological trajectories. *Research Policy* 11:147-162.

Dosi, Giovanni, Franco Malerba, Giovanni B. Ramello, and Francesco Silva. 2006. Information, appropriability, and the generation of innovative knowledge four decades after Arrow and Nelson: an introduction. *Ind Corp Change* 15 (6):891-901.

Dubin, Jeffrey A., and Douglas Rivers. 1989. Selection Bias in Linear Regression, Logit and Probit Models. *Sociological Methods and Research* 18 (2):360-90.

Dyer, Jeffrey H., and Kentaro Nobeoka. 2000. Creating and Managing a High-Performance Knowledge-Sharing Network: The Toyota Case. *Strategic Management Journal* 21 (3):345.

Eisenhardt, Kathleen M., and Jeffrey A. Martin. 2000. Dynamic Capabilities: What Are They? *Strategic Management Journal* 21 (10/11):1105-1121.

Fleming, Lee. 2001. Recombinant Uncertainty in Technological Search. *Management science* 47 (1):117.

Fleming, Lee, and Olav Sorenson. 2001. Technology as a complex adaptive system: evidence from patent data. *Research Policy* 30 (7):1019-1039.

Fontana, Roberto, Aldo Geuna, and Mireille Matt. 2006. Factors affecting university-industry R&D projects: The importance of searching, screening and signalling. *Research Policy* 35:309-323.

Fosfuri, Andrea. 2004. The Licensing Dilemma: Understanding the Determinants of the Rate of Licensing. In *Universidad Carlos III De Madrid*.

Gambardella, Alfonso, Paola Giuri, and Alessandra Luzzi. 2007. The market for patents in Europe. *Research Policy* 36 (8):1163-1183.

Gans, Joshua S., David H. Hsu, and Scott Stern. 2002. When does start-up innovation spur the gale of creative destruction? *RAND Journal of Economics* 33 (4):571-586.

———. 2006. The Impact of Uncertain Intellectual Property Rights on the Market For Ideas: Evidence From Patent Grant Delays: National Bureau of Economic Research Cambridge, Mass., USA.

———. 2007. The Impact of Uncertain Intellectual Property Rights on the Market For Ideas: Evidence From Patent Grant Delays: National Bureau of Economic Research Cambridge, Mass., USA.

Gans, Joshua S., and Scott Stern. 2003. The product market and the market for "ideas": commercialization strategies for technology entrepreneurs. *Research Policy* 32 (2):333-350.

Gilbert, Richard J., and David M. G. Newbery. 1982. Preemptive Patenting and the Persistence of Monopoly. *American Economic Review* 72 (3):514.

Giuri, Paola, Myriam Mariani, Stefano Brusoni, Gustavo Crespi, Dominique Francoz, Alfonso Gambardella, Walter Garcia-Fontes, Aldo Geuna, Raul Gonzales, Dietmar Harhoff, Karin Hoisl, Christian Le Bas, Alessandra Luzzi, Laura Magazzini, Lionel Nesta, Onder Nomaler, Neus Palomeras, Pari Patel, Marzia Romanelli, and Bart Verspagen. 2007. Inventors and invention processes in Europe: Results from the PatVal-EU survey. *Research Policy* 36 (8):1107-1127.

Granovetter, Mark. 1973. The strength of weak ties. *American Journal of Sociology* 78 (6):1360-1380.

———. 1985. Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology* 91 (3):481-510.

Grimpe, Christoph, and Katrin Hussinger. 2008. Building and Blocking: The Two Faces of Technology Acquisition. *ZEW Discussion Paper* 08-042.

Grindley, Peter C, and David J. Teece. 1997. Managing intellectual capital: Licensing and cross-licensing in semiconductors and electronics. *California Management Review* 39 (2):8-41.

Gulati, Ranjay. 1999. Network location and learning: the influence of network resources and firm capabilities on alliance formation. *Strategic Management Journal* 20 (5):397-420.

Gulati, Ranjay, and Monica C. Higgins. 2003. Which ties matter when? the contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal* 24 (2):127-144.

Gulati, Ranjay, and Harbir Singh. 1998. The Architecture of Cooperation: Managing Coordination Costs and Appropriation Concerns in Strategic Alliances. *Administrative Science Quarterly* 43 (4):781-814.

Gulati, Ranjay, and Maxim Sytch. 2007. Dependence Asymmetry and Joint Dependence in Interorganizational Relationships: Effects of Embeddedness on a Manufacturer's Performance in Procurement Relationships. *Administrative Science Quarterly* 52 (1):32-69.

Hall, Bronwyn H. 1990. The Manufacturing Sector Master File: 1959-1987. *NBER Working Paper* 3366.

———. 2004. Exploring the Patent Explosion. *Journal of Technology Transfer* 30 (1):35-48.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools: NBER.

Hall, Bronwyn H., and Rosemarie Ham Ziedonis. 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979-1995. *RAND Journal of Economics* 32 (1):101-128.

Hannan, Michael T., and John Freeman. 1977. The Population Ecology of Organizations. *American Journal of Sociology* 82 (5):929-964.

Harabi, Najib. 1995. Appropriability of technical innovations an empirical analysis. *Research Policy* 24 (6):981-992.

Harhoff, Dietmar, Francis Narin, Frederic M. Scherer, and Katrin Vopel. 1999. Citation Frequency and the Value of Patented Inventions. *Review of Economics & Statistics* 81 (3):511-515.

He, Zi-Lin, and Min Deng. 2007. The evidence of systematic noise in non-patent references: A study of New Zealand companies' patents. *Scientometrics* 72 (1):149-166.

Heckman, James J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47 (1):153.

Heller, Michael A., and Rebecca S. Eisenberg. 1998. Can patents deter innovations? The anticommons in biomedical research. *Science* 280 (5364):698-701.

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

Hoerner, Robert J. 1984. Patent Misuse. *Antitrust Law Journal* 53 (4):641-662.

Hu, Li-tze, and Peter M. Bentler. 1999. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus. *Structural Equation Modeling* 6 (1):1.

Hurmelinna-Laukkanen, Pia, and Kaisu Puumalainen. 2007. Nature and dynamics of appropriability: strategies for appropriating returns on innovation. *R&D Management* 37 (2):95-112.

Jacobides, Michael G., and Sidney G. Winter. 2005. The co-evolution of capabilities and transaction costs: explaining the institutional structure of production. *Strategic Management Journal* 26 (5):395-413.

Jaffe, Adam B. 2000. The U.S. patent system in transition: policy innovation and the innovation process. *Research Policy* 29:531-557.

Jaffe, Adam B., Manuel Trajtenberg, and Michael S. Fogarty. 2000. Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. *American Economic Review* 90 (2):215-218.

Jensen, Richard, and Marie Thursby. 2001. Proofs and Prototypes for Sale: The Licensing of University Inventions. *American Economic Review* 91 (1):240-259.

Kamien, Morton I., and Nancy L. Schwartz. 1975. Market Structure and Innovation: A Survey. *Journal of Economic Literature* 13 (1):1.

Kamien, Morton I., and Nancy Lou Schwartz. 1982. *Market structure and innovation*, *Cambridge surveys of economic literature*. Cambridge: Cambridge University Press.

Kash, D. E., and W. Kingston. 2001. Patents in a world of complex technologies. *Science and Public Policy* 28:11-22.

Katila, Riitta. 2002. New product search over time: Past ideas in their prime? *Academy of Management Journal* 45 (5):995-1010.

Katila, Riitta, and Gautam Ahuja. 2002. Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Development. *Academy of Management Journal* 45 (6):1183-1194.

Katz, Michael L., and Carl Shapiro. 1994. Systems Competition and Network Effects. *Journal of Economic Perspectives* 8 (2):93-115.

Kim, YoungJun, and Nicholas S. Vonortas. 2006. Determinants of technology licensing: the case of licensors. *Managerial and Decision Economics* 27 (4):235-249.

Klein, Benjamin, Robert G. Crawford, and Armen A. Alchian. 1978. Vertical Integration, Appropriable Rents, and the Competitive Contracting Process. *Journal of Law and Economics* 21 (2):297-326.

Kogut, Bruce, and Udo Zander. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science* 3 (3):383-397.

———. 2003. Knowledge of the firm and the evolutionary theory of the multinational corporation. *Journal of International Business Studies* 34 (6):516.

Kollmer, Holger, and Michael Dowling. 2004. Licensing as a commercialisation strategy for new technology-based firms. *Research Policy* 33 (8):1141-1151.

Kortum, Samuel, and Josh Lerner. 1999. What is behind the recent surge in patenting? *Research Policy* 28 (1):1-22.

Kuhn, Thomas S. 1970. *The Structure of Scientific Revolutions*: University Of Chicago Press.

Kusunoki, Ken, Ikujiro Nonaka, and Akiya Nagata. 1998. Organizational Capabilities in Product Development of Japanese Firms: A Conceptual Framework and Empirical Findings. *Organization Science* 9 (6):699.

Lafontaine, Francine, and Margaret Slade. 2007. Vertical Integration and Firm Boundaries: The Evidence. *Journal of Economic Literature* 45:629-685.

Lane, Peter J., and Michael Lubatkin. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* 19 (5):461.

Langinier, Corinne. 2005. Using patents to mislead rivals. *Canadian Journal of Economics/Revue canadienne d'economique* 38 (2):520-545.

Lanjouw, Jean Olson, Ariel Pakes, and Jonathan Putnam. 1998. How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data. *Journal of Industrial Economics* 46 (4):405-432.

Lanjouw, Jean Olson, and Mark Schankerman. 2004. Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. *Economic Journal* 114 (495):441-465.

Laursen, Keld, and Ammon J. Salter. 2004. Searching high and low: what types of firms use universities as a source of innovation? *Research Policy* 33:1201-1215.

———. 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal* 27 (2):131-150.

Lemley, Mark A., and Carl Shapiro. 2005. Probabilistic Patents. *Journal of Economic Perspectives* 19 (2):75-98.

———. 2007. Patent Holdup and Royalty Stacking. *Texas Law Review* 85:1991-2049.

Levin, Richard C. 1988. Appropriability, R&D Spending, and Technological Performance. *American Economic Review* 78 (2):424.

Levin, Richard C., Wesley M. Cohen, and David C. Mowery. 1985. R & D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses. *American Economic Review* 75 (2):20.

Levin, Richard C., Alvin K. Klevorick, Richard R. Nelson, Sidney G. Winter, Richard Gilbert, and Zvi Griliches. 1987. Appropriating the Returns from Industrial Research and Development. *Brookings Papers on Economic Activity* 1987 (3):783-831.

Levinthal, Daniel, and James G. March. 1993. The myopia of learning. *Strategic Management Journal* 14:95-112.

Levitt, Barbara, and James G. March. 1988. Organizational Learning. *Annual Review of Sociology* 14:319-340.

Link, Albert L., and John Rees. 1990. Firm Size, University Based Researc, and the Returns to R&D. *Small Business Economics* 2:25-31.

Long, J. Scott, and Jeremy Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*: Stata Press.

Malerba, Franco, and Luigi Orsenigo. 1995. Schumpeterian patterns of innovation. *Cambridge Journal of Economics* 19 (1):47-65.

Mansfield, Edwin. 1964. Industrial Research and Development Expenditures: Determinants, Prospects, and Relation to Size of Firm and Inventive Output. *Journal of Political Economy* 72 (4):319-340.

March, James G. 1991. Exploration and Exploitation in Organizational Learning. *Organization Science* 2 (1):71-87.

Merges, Robert P. 1994. Intellectual Property Rights and Bargaining Breakdown: The Case of Blocking Patents. *Tennessee Law Review* 62:75-106.

Moser, Petra, and Alessandra Voena. 2009. Compulsory Licensing: Evidence from the Trading with the Enemy Act. In *The Oliver E. Williamson Seminar on Institutional Analysis*. University of California, Berkeley.

Murmann, Johann Peter, and Koen Frenken. 2006. Toward a systematic framework for research on dominant designs, technological innovations, and industrial change. *Research Policy* 35 (7):925-952.

Nagaoka, Sadao, and Hyeong Ug Kwon. 2006. The incidence of cross-licensing: A theory and new evidence on the firm and contract level determinants. *Research Policy* 35 (9):1347-1361.

Nelson, Richard R., and Sidney G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, Mass.: Harvard University Press.

Nerkar, Atul, and Peter W. Roberts. 2004. Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. *Strategic Management Journal* 25 (8-9):779-799.

Nerkar, Atul, and Scott Shane. 2007. Determinants of invention commercialization: an empirical examination of academically sourced inventions. *Strategic Management Journal* 28 (11):1155-1166.

Nonaka, Ikujiro, Ryoko Toyama, and Akiya Nagata. 2000. A firm as a knowledge-creating entity: a new perspective on the theory of the firm. *Industrial and Corporate Change* 9 (1):1-20.

Norton, Edward C., Hua Wang, and Chunrong Ai. 2004. Computing interaction effects and standard errors in logit and Probit models. *Stata Journal* 4 (2):154-167.

Nunnally, J. C. 1978. *Psychometric theory*. New York: McGraw-Hill.

OECD. 2006. The OECD Database on Triadic Patent Families. (December 2006).

OECD, Committee for Scientific and Technological Policy (Ed.). 2003. Preliminary Results of OECD/BIAC Survey on the Use and Perception of Patents in the Business Community. In *Working Party on Innovation and Policy*.

Owen-Smith, Jason. 2003. From separate systems to hybrid order: accumulative advantage across public and private science at Research One universitis. *Research Policy* 32:1081-1104.

Owen-Smith, Jason, and Walter W. Powell. 2004. Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organization Science* 15 (1):5-21.

Oxley, Joanne E. 1997. Appropriability Hazards and Governance in Strategic Alliances: A Transaction Cost Approach. *Journal of Law, Economics, & Organization* 13 (2):387-409.

———. 1999. Institutional environment and the mechanisms of governance: the impact of intellectual property protection on the structure of inter-firm alliances. *Journal of Economic Behavior & Organization* 38 (3):283-309.

Pavitt, Keith, M. Robson, and J. Townsend. 1987. The Size Distribution of Innovating Firms in the UK: 1945-1983. *Journal of Industrial Economics* 35 (3):297-316.

Peteraf, Margaret A. 1993. The Cornerstones of Competitive Advantage: A Resource-Based View. *Strategic Management Journal* 14 (3):179-191.

Pisano, Gary. 2006. Profiting from innovation and the intellectual property revolution. *Research Policy* 35 (8):1122-1130.

Pisano, Gary P. 1990. The R&D Boundaries of the Firm: An Empirical Analysis. *Administrative Science Quarterly* 35 (1):153-176.

Podolny, Joel M., and Karen L. Page. 1998. Network Forms of Organization. *Annual Review of Sociology* 24 (1):57-76.

Powell, Walter W. 1990. Neither market nor hierarchy: network forms of organization. In *Research in Organizational Behavior*, edited by B. Staw and L. L. Cummings. Greenwich, CT: JAI Press.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr. 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. *Administrative Science Quarterly* 41 (1):116-145.

Reitzig, Markus. 2004. The private values of 'thickets' and 'fences': towards an updated picture of the use of patents across industries. *Economics of Innovation & New Technology* 13 (5):457-476.

Rigby, Darrell, and Chris Zook. 2002. Open-Market Innovation. *Harvard Business Review* 80 (10):80-89.

Rivette, Kevin G., and David Kline. 2000. *Rembrandts in the Attic: Unlocking the Hidden Value of Patents*: Harvard Business School Press.

Roberts, Edward B. 1988. Managing Invention and Innovation. *Research Technology Management* 31 (1):11-27.

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

Rothaermel, Frank T., and David L. Deeds. 2004. Exploration and Exploitation Alliances in Biotechnology: A System of New Product Development. *Strategic Management Journal* 25:201-221.

———. 2006. Alliance type, alliance experience and alliance management capability in high-technology ventures. *Journal of Business Venturing* 21 (4):429-460.

Rothwell, R., C. Freeman, A. Horlsey, V. T. P. Jervis, A. B. Robertson, and J. Townsend. 1974. SAPPHO updated - project SAPPHO phase II. *Research Policy* 3 (3):258-291.

Sanders, Barkev S., Joseph Rossman, and L. James Harris. 1958. Economic Impact of Patents. *Patent, Trademark and Copyright Journal of Research and Education* 2 (3):340.

Saunders, Kurt M. 2002. Patent Nonuse and the Role of Public Interest as a Deterrent to Technology Suppression. *Harvard Journal of Law & Technology* 15 (2):389-452.

Scherer, F. M. 1965. Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. *American Economic Review* 55 (5):1097-1125.

———. 1983. The Propensity to Patent. *International Journal of Industrial Organization* 1:107-128.

Scherer, Frederic M., and D. Ross. 1990. *Industrial market structure and economic performance*. Boston: Haughton Miffin.

Schmookler, Jacob. 1954. The Level of Inventive Activity. *Review of Economics & Statistics* 36 (2):183.

Schumpeter, Joseph A. 1934. *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Translated by R. Opie. Galaxy Book, 1961 ed. New York: Oxford University Press.

———. 1939. *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process*. Vol. I. New York: McGraw-Hill.

———. 1942. *Capitalism, Socialism and Democracy*: HarperPerennial.

Shan, Weijan, Gordon Walker, and Bruce Kogut. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. *Strategic Management Journal* 15 (5):387-394.

Shane, Scott. 2001. Technology Regimes and New Firm Formation. *Management Science* 47 (9):1173-1190.

———. 2009. The Likely Adverse Effects of an Apportionment-Centric System of Patent Damages. In *Public Hearings Concerning the Evolving Intellectual Property Marketplace*. Washington, D.C.: Federal Trade Commission.

Shapiro, Carl. 2000. Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting. In *Innovation Policy and the Economy*. Washington, D.C.: NBER.

Sheehan, Jerry, Catalina Martinez, and Dominique Guellec. 2003. Understanding business patenting and licensing: Results of a survey. In *OECD Conference on Intellectual Property Rights, Innovation and Economic Performance* Paris: OECD.

Soete, Luc L. G. 1979. Firm size and inventive activity : The evidence reconsidered. *European Economic Review* 12 (4):319-340.

Somaya, Deepak, and David J. Teece. 2001. Combining Patent Inventions in Multi-Invention Products: Transactional Challenges and Organizational Choices. *University of California at Berkeley Working Paper*.

Stuart, Toby E., Ha Hoang, and Ralph C. Hybels. 1999. Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly* 44:315-349.

Teece, David J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* 15 (6):285-305.

———. 2006. Reflections on "Profiting from Innovation". *Research Policy* 35 (8):1131-1146.

Teece, David J., Gary P. Pisano, and Amy Shuen. 1997. Dynamic Capabilities and Strategic Management. *Strategic Management Journal* 18 (7):509-533.

Thomas, John R. 2007. Prepared Statement of John R. Thomas. In *Hearing on "The Patent Reform Act of 2007"*: U.S. House of Representatives Subcommittee on Courts, the Internet, and Intellectual Property.

Tong, Xuesong, and J. Davidson Frame. 1994. Measuring national technological performance with patent claims data. *Research Policy* 23:133-141.

Train, Kenneth. 2003. *Discrete Choice Methods with Simulation*. Cambridge, MA: Cambridge University Press.

Tsai, Kuen-Hung. 2005. R&D productivity and firm size: a nonlinear examination. *Technovation* 25 (7):795-803.

Tsai, Kuen-Hung, and Jiann-Chyuan Wang. 2005. Does R&D performance decline with firm size?--A re-examination in terms of elasticity. *Research Policy* 34 (6):966-976.

Turner, Julie S. 1998. Nonmanufacturing Patent Owner: Toward a Theory of Efficient Infringement, The. *California Law Review* 86:179-210.

Tushman, Michael L., and Philip Anderson. 1986. Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly* 31:439-465.

U.S. Census Bureau. 2006. 2002 Economic Census: Survey of Business Owners. Washington, D.C.: U.S. Department of Commerce.

Utterback, James M. 1994. *Mastering the Dynamics of Innovation*. Boston, MA: Harvard Business School Press.

Uzzi, Brian. 1996. The sources and consequences of embeddedness for the economic performance of organizations: the network effect. *American Sociological Review* 61 (4):674-698.

———. 1997. Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly* 42 (1):37-69.

van Zeebroeck, Nicolas, Niels Stevnsborg, Bruno van Pottelsberghe de la Potterie, Dominique Guellec, and Eugenio Archontopoulos. 2008. Patent inflation in Europe. *World Patent Information* 30 (1):43-52.

van Zeebroeck, Nicolas, Bruno van Pottelsberghe de la Potterie, and Dominique Guellec. 2006. Claiming more: the increased voluminosity of patent applications and its

determinants: Universite Libre de Bruxelles, Solvay Business School, Centre Emile Bernheim (CEB).

Veugelers, Reinhilde, and Bruno Cassiman. 1999. Make and buy in innovation strategies: evidence from Belgian manufacturing firms. *Research Policy* 28 (1):63-80.

von Hippel, Eric. 1988. *The Sources of Innovation*: Oxford University Press.

———. 1994. "Sticky Information" and the Locus of Problem Solving: Implications for Innovation. *Management Science* 40 (4):429-439.

Wade, James. 1995. Dynamics of Organizational Communities and Technological Bandwagons: An Empirical Investigation of Community Evolution in the Microprocessor Market. *Strategic Management Journal* 16 (Special Issue):111-133.

Whinston, Michael D. 2003. On the Transaction Cost Determinants of Vertical Integration. *Journal of Law, Economics, and Organization* 19 (1):1.

Williamson, Oliver E. 1979. Transaction-Cost Economics: The Governance of Contractural Relations. *Journal of Law and Economics* 22 (2):233-61.

———. 1981. The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology* 87 (3):548-577.

———. 1985. *The Economic Institutions of Capitalism: Firms, markets, relational contracting*. New York: Free Press.

———. 1991. Comparative Economic Organization: The Analysis of Discrete Structural Alternatives. *Administrative Science Quarterly* 36 (2):269-296.

———. 2002. The Theory of the Firm as Governance Structure: From Choice to Contract. *Journal of Economic Perspectives* 16:171-195.

Winter, Sidney G. 2006. The logic of appropriability: From Schumpeter to Arrow to Teece. *Research Policy* 35 (8):1100-1106.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: MIT Press.

Ziedonis, Rosemarie Ham. 2004. Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms. *Management Science* 50 (6):804-820.

Zucker, L. G., M. R. Darby, and J. S. Armstrong. 2002. Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. *Management Science* 48 (1):138-153.

Zucker, Lynne G., and Michael R. Darby. 1996. Star Scientists and Institutional Transformation: Patterns of Invention and Innovation in the Formation of the Biotechnology Industry. *Proceedings of the National Academy of Sciences of the United States of America* 93 (23):12709-12716.

Zucker, Lynne G., Michael R. Darby, and Marilynn B. Brewer. 1998. Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises. *American Economic Review* 88 (1):290-306.

VITA

Taehyun Jung was born and grew up in Seoul, Korea. He started the Joint Ph.D. Program in public policy of the School of Public Policy, Georgia Tech and Andrew Young School of Policy Studies at Georgia State University in 2003. Before he joined the doctoral program, he had worked for IBM as a business and IT consultant. He received M.A. in Economics from Yonsei University and M.Sc. in Physics from Seoul National University. Since August 2008, he has been working as a scientific researcher at the Fraunhofer Institute for Systems and Innovation Research (ISI) in Germany.