EXPANDING UNDERSTANDING OF THE INNOVATION PROCESS:

R&D AND NON-R&D INNOVATION

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EXPANDING UNDERSTANDING OF THE INNOVATION PROCESS:

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SUMMARY

While most innovation research is centered on R&D activity, there is growing awareness of other forms of innovative activity. Recent work on European firms finds that almost half of innovators do no formal R&D (Arundel et al., 2008; Huang et al., 2011). Data from the 2011 NSF BRDI Survey suggest that 72% of product innovating firms are non-R&D performing firms (NSF, 2014). Although these are the firm-level (not innovation-level) statistics, the results suggest that non-R&D innovation may be an important complement to R&D-based innovation in the contemporary innovation system. Until now, there are few studies on non-R&D-based innovation in the US. Given the prevalence of such innovators suggested in the new NSF statistics, there is a need to broaden our research focus and develop our understanding of non-R&D innovation to complement existing work on R&D-based innovation. Given limited work in this area (especially from the US), this dissertation maps the rates of non-R&D inventions and innovations, provides an opportunity to develop theories of the organization of innovation, and contributes to the science of science and innovation policy by expanding the domain of study. The goal is to generate more realistic theories and appropriate measures of the innovation process that integrate both R&D and non-R&D-based innovative activity into the overall innovation system. Chapter 1 develops the problem and lays out the goals of this project and the research in furtherance of these goals is presented across four chapters (Chapters 2, 3, 4 and 5).

Innovation is a key but poorly understood concept in management, economics, sociology and public policy. The uses and measures of the concept also vary across studies. Furthermore, drawing on the different understandings of the meaning of innovation, the various streams of innovation research tend to focus on one or another aspect of the innovation process. Chapter 2

examines how innovation is defined in different theories: growth theory, creativity theory, and diffusion theory, and shows the lack of consensus about the conceptualization of innovation and the differences in the foregrounded aspects of the innovation process.

Innovation is studied with different measures reflecting one or another aspect of the innovation process. Science, Technology and Innovation (STI) policymakers have struggled with the problem of how to develop STI indicators that capture innovative activity in the contemporary US economy. Drawing on the current status of STI indicator studies, Chapter 3 reviews and evaluates a variety of commonly-used innovation indicators such as R&D, patents, and innovation. Then, using data from multiple data sources such as USPTO patent data, NSF surveys, private US innovation survey data, and German Community Innovation Survey data, this chapter examines the overlap and differences across these indicators. Furthermore, this study suggests the need for a broader understanding of innovation and introduces new measures that complement existing measures to better capture the full population of innovation. These new measures focus on the distinction between innovations originating from R&D and those from outside of R&D (non-R&D innovation). We find that 12% of triadically patented inventions come from non-R&D. And, even among R&D performing manufacturing firms, almost 10% of new to market innovations are non-R&D. This study contributes to better conceptualizing innovation by cross-validating innovation indicators, developing innovation indicators beyond the R&D-based perspective on innovation, and emphasizing the importance of understanding the broad universe of innovative activity.

Motivated by Chapter 3, Chapter 4 analyzes R&D and non-R&D innovation in terms of variation of learning environments. As Simon (1976) pointed out, "Intuition, judgment, creativity are basically expressions of capabilities for recognition and response based upon experience and

knowledge." Workers gain experience and knowledge in the course of their normal jobs. Therefore, innovative ideas can be generated from knowledge built from learning opportunities across the firm (not just the R&D lab). Employees working for different functions (R&D and outside of R&D) in an organization have different work practices and build their learning through different processes. Moreover, the relative effectiveness of learning by different work practices for innovation is contingent on nature of knowledge, characterized by generality and visibility. Using multiple datasets combining public and private data and focusing on births of innovations, this study shows how nature of knowledge affects differences in the innovation productivity of R&D and non-R&D activity. The chapter concludes with a discussion of the implications of these insights for innovation management and policy.

New ideas can be used internally, but also can be traded to other users in the market through M&A, joint venture, licensing and so on. Focusing on licensing, Chapter 5 analyzes how inventions managed by different licensing structures participate in the market for technology. Technology licensing can be an important part of a firm's innovation strategy. Most of the focus in the literature has been on how firm and market characteristics affect licensing activity. However, in the field of strategic management of licensing, there is also a need to understand how licensing activity should be organized within firms beyond firm- and market-level approaches. Using invention-level licensing data, this study reports empirical evidence for a theoretical model of organizing licensing in firms. Given the separate stages of willing to license and being actually licensed given willing to license, this study focuses on the stage of willing to license and tests the effect of different licensing management structures (i.e., centralized vs. decentralized) on the probability of firms' joining the licensing market with their inventions. Furthermore, inventions associated with different organization of licensing have important

effects on the structuring of the licensing contract, such that firms will try to put restrictions in the licensing contract (exclusivity clauses). The results suggest that firms build different strategies for licensing of the different technological inventions generated. The results add empirical evidence to, and advance, a recent theoretical model of the organization of licensing.

Lastly, Chapter 6 discusses the implications and contributions of the overall work to expanding understanding of the innovation process.

CHAPTER 1

OVERALL RESEARCH GOALS

Innovation is widely recognized as a key to economic growth (Romer, 1990; Rosenberg, 1982).

Most research on the innovation process has focused on the results of R&D projects (Cohen,

2010). The positive relation between R&D intensity as an input and innovative performance as

an output has become the canonical image for research on innovation (Cockburn and Griliches,

1987; Wakelin, 2001). While R&D is an important input to innovation, there is growing

evidence that a significant share of innovation is not born from R&D (Arundel et al., 2008).

Much of this non-R&D innovation consists of incremental improvements to existing products, or

process innovations, although non-R&D innovation is not limited to these kinds of

improvements. Rosenberg (1982) shows that a significant share of product development and

improved productivity comes from the accumulation of such innovations, often generated by

craftsmen and mechanics solving problems in their daily operations. Non-R&D innovations can

also come from problem solving activities or pursuit of new product ideas outside of a formal

R&D project. Such activities would be missed in innovation accounts based on regular, formal

R&D. Given the importance of innovation for the sociology and economics of science, and the

central role of innovation in policy debates, this dissertation expands the study of innovation to

include non-R&D innovations and analyzes the drivers and outcomes of non-R&D compared to

R&D-based innovations, with the goal of improving science and innovation policy by creating

new measures and improving understanding of existing measures, and by developing new

models of the innovation process that expand beyond the existing emphasis on R&D inputs and

patent outputs. The work to achieve this goal is laid out across chapters. The results will help

guide science and innovation policy, and guide firm strategy for developing different types of inventions and commercializing those different inventions.

CHAPTER 2

VARIATION IN THE CONCEPT OF INNOVATION: A REVIEW OF THE LITERATURE

2.1. Introduction

Innovation is a key but poorly understood concept in management, economics, sociology and public policy. One can see a variety of uses of the term "innovation" in the literature, and also a proliferation of measures even among those who share underlying concepts. Gopalakrishnan and Damanpour (1997) characterize how researchers in each discipline conceptualize innovation differently reviewing innovation studies in sociology, engineering, economics, marketing and psychology. Based on their review of the literature, they discuss the discipline-based perspectives in innovation studies in terms of stages of the innovation process (e.g., generation or adoption), levels of analysis and type of innovation, although with limited discussion of what innovation by itself means in each discipline. Fagerberg (2003) shows that different disciplines deal with the different aspects of innovation, such as economic growth and networks, with the definitions of invention as "the first occurrence of an idea for a new product or process" and innovation as "the first commercialization of the idea". However, grounded in this initial work, there is still a need to map and clarify the uses of the term, "innovation", and its various indicators, in order to facilitate innovation studies that are focusing on the drivers and outcomes of something called "innovation." This chapter reviews the literature on innovation focusing on the various meanings of "innovation" from different theoretical perspectives (e.g., growth theory, creativity theory, and diffusion theory) and shows the lack of consensus about the

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conceptualization of innovation and the differences in the foregrounded aspects of the innovation process.

2.2. Conceptualizing innovation on the different theoretical perspectives

According to the Oslo manual (OECD, 2005), an innovation is defined as "*the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations*." Many innovation studies have used slight modifications of this definition as their starting point. Although innovation scholars often use this definition, there is no actual consensus about the meaning of innovation among scholars or across disciplines, as can be seen by their uses of the term in their theoretical and empirical work. In this section, we examine the meaning of innovation as discussed in different theoretical perspectives.

2.2.1. Innovation and growth theory

Although innovation can be defined and interpreted differently by scholars, their common starting point is Schumpeter. Schumpeter (2008) argues that the engine of capitalism is production for the mass market and this engine is kept in motion by creative destruction, i.e., the continuous process of generating new products, processes, markets and organizational forms that make existing ones obsolete. Thus, for Schumpeter, innovation is the setting up of a new production function through the process of creative destruction (Schumpeter, 1939). Creating new ways of production, as well as new products, is an important driver of economic growth. Rosenberg (2004) shows that increasing inputs accounts for a small portion of the actual growth (about 15%) and the rest of growth comes from creating new ways to produce more output from

the same number of inputs. Although Schumpeter (2008)'s concept innovation covers more broadly including organizational change in the process of creative destruction, innovation has most often been discussed in terms of the technological change causing economic growth. Advancing Solow (1956)'s exogenous technological change theory, Romer (1986, 1990) develops a long-run growth model with endogenous technological change through accumulation of knowledge and a large amount of human capital (as distinct from simply a large population). According to Romer (1990), technological change means "improvement in the instructions for mixing raw materials" which features increasing marginal productivity. Although raw materials are not changed, the instructions of combining those can be improved through trial and error, experimentation, refinement, and scientific investigation (Romer, 1990). He provides an example that iron oxide was used as a pigment before, but now is painted onto plastic tape and used to produce videocassette recordings. Thus, the meaning of innovation by economic growth theorists is *technological change that yields more or better output from a given bundle of inputs*. In this conceptualization, the term innovation can be equated with technological innovation. However, types of innovation (e.g., product or process, radical or incremental) are less of interest as long as they improve efficiency or quality in production. Innovation, or technological improvement, in growth theory is endogenously driven by accumulation of knowledge. The stock of knowledge in Romer's production function is a result of expenditure on research and development, and thus, R&D has been considered a main driver of economic growth (Mansfield, 1972; Romer, 1986, 1994). However, Mansfield (1972) points out that economists see the rest of the measured economic growth not explained by such inputs as labor and capital as attributed to technological change, which prevents them from capturing the correct isolated effect of technological change, and leads them to consider the effect of technological change and that of R&D as equivalent,

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although much of the nation's R&D is devoted to increasing other national purposes such as defense that are not captured by growth of national income. The direct relation between R&D and productivity increase shows that R&D expenditures are concentrated in a few industries and mostly produce modest advances in technology (Mansfield, 1972). Extending Romer's growth model with human capital, or skill, accumulation, Sorensen (1999) shows that R&D is unprofitable when the levels of human capital are low, because the return to innovation cannot outweigh the return to investing in learning, which is relatively more important for productivity increase, whereas R&D becomes profitable for higher levels of human capital. R&D also has distinct roles between innovation and imitation (Davidson and Segerstrom, 1998; Griffith et al., 2004). Davidson and Segerstrom (1998) argue that innovation rates increase with innovative R&D for developing higher-quality products, leading to faster economic growth, but decrease with imitative R&D for producing copies or differentiated versions of those products because increasing imitation rates make monopoly profits short-lived. In general, higher R&D subsidies increase world growth rate by stimulating innovative R&D efforts (Davidson and Segerstrom, 1998). Although developed or technological frontier countries do more innovative R&D than developing countries or countries behind the technological frontier (Davidson and Segerstrom), Griffith et al. (2004) see that the technology transfer from advanced to less advanced countries would contribute to growth of all countries.

Industrial organization economists, viewing total R&D effort as innovativeness or rate of technological progress, have examined drivers of R&D in terms of firm and industrial characteristics (Cohen, 2010). For example, Cohen and Klepper (1996b) argue that large firms spend more on R&D than small firms because larger firms have the greater level of output to which they can apply the results of R&D, spreading the costs of R&D over a larger base.

Furthermore, R&D cost spreading in larger firms raises the share of process R&D undertaken relatively more than that of product R&D (Cohen and Klepper, 1996a; Klepper, 1996). Cohen and Klepper (1996a) provide the following implication for the composition of R&D between process and product by firm size: product innovation creates immediate and greater returns from licensing or sales in a disembodied form, and, thereby, is less affected by firm size than process innovation with its R&D cost spreading advantage. However, firm size can have negative effects on innovative activity, or R&D, due to bureaucratization suppressing creativity and difficulty of direct observation of individual scientists' effort diminishing their incentives (Ahuja et al., 2008). Moreover, while firm diversification may encourage R&D due to greater financial resources, effective spreading of the risk of failure, and multiple domains for applying results, it can prevent firms from monitoring individual divisions and create information overload and reluctance to invest in risky activities irrelevant to the individual division (Ahuja et al., 2008; Doi, 1985). In addition to firm size and diversification, market structure and innovative activity have also been an important topic, based on the Schumpeterian perspective of a positive relationship between monopolization and innovative activity. Blundell et al. (1999) show that incumbent monopolists not only have higher cash flows for financing investment in R&D, but also greater incentive to search for innovations for obtaining a higher stock market value. However, Scherer (1967) and Sutton (1996) show that the positive relationship between market concentration and industrial inventive and innovative effort, or R&D, becomes modest after controlling technology opportunity, because of the correlation between concentration and technology opportunity. Moreover, in the industries with relatively low concentration, technological competition increases with concentration, thereby eliciting more innovative efforts (i.e., increasing employment of scientists and engineers) while in industries with high

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concentration, additional market power becomes an unimportant stimulus for innovative efforts (Scherer, 1967). However, Geroski (1990) argues that actual monopoly may not stimulate innovative activity strongly or positively because incumbent monopolists may suffer from behavioral disadvantages from managerial laziness, bureaucratic inertia, and inefficiency and depend on previous innovations which create a lower net return from introducing a new innovation, encouraging entrants' activities. Aghion et al. (2005) also argue that an increase in product market competition stimulates firms' R&D and innovation in order to escape competition, thereby generating productivity growth, and eventually, technology progress from the process of "step-by-step" innovation. Reversing the prediction of concentration increasing with technological progressiveness in industries driven by the Schumpeterian perspective, Mukhopadhyay (1985) illustrates that, allowing entry, technological progress (i.e., high propensity to spend on R&D) has a negative effect on market concentration because the net rate of entry is much higher in technologically progressive industries. In addition, other industrial characteristics such as learning environments and effectiveness of appropriability increasing monopoly power or spillovers also have been important factors to drive R&D activity (Cohen and Levinthal, 1989; Cohen and Walsh, 2000).

Thus, in the innovation and growth perspective, innovation is seen as a key source of growth, with a significant endogenous component. Much of the research sees R&D as the key proxy for innovation and focuses on organizational context factors such as size and market concentration that promote R&D efforts.

2.2.2. Innovation and creativity theory

Firm and industrial characteristics, which are important drivers of innovation, are expressed through the actions of individuals and groups in an organization. Creativity theory argues that the innovation process starts from generating ideas, and focuses on which individuals under what circumstances effectively use available resources creatively (Brennan and Dooley, 2005; McAdam and McClelland, 2002). Creativity is defined as a novel, useful, and appropriate response to the task or problem and considered a source of competitive advantage (Amabile, 1983, 1996; McAdam and McClelland, 2002). West (2002) and Yusuf (2009) argue that creativity is thinking about new things or making a new combination of existing elements. This process often builds on networks of those with different perspectives and learning societies to share knowledge, with innovation as the implementation and eventual commercialization of the new ideas. Brennan and Dooley (2005) and Tang (1998) argue that creativity is a relatively more individual and solitary process based on personal ability to recognize unusual and novel relations of things and a prerequisite for innovation while innovation is a more inclusive and complicated social process involving many people. Although creativity may have various definitions, it shares some common themes such as novelty, appropriateness, originality and far-reachingness and innovation as the organizational implementation of those creative ideas (DiLiello and Houghton, 2006). However, Baer (2012) treats innovation as an umbrella concept including creativity and implementation. Creativity, as a sub-process of innovation, is the development of novel and useful ideas, and its implementation refers to the translation of the ideas into new and improved products or ways of doing things, all of which is encompassed by the concept of innovation (Baer, 2012; Hülsheger et al., 2009). Thus, creativity has been investigated as either a separate and prerequisite concept of innovation or a component of innovation as an umbrella concept.

However, in either case, in creativity theory, innovation does not exist without creativity, and thereby can be conceptualized broadly as *generation and implementation of a novel and useful idea* in an organization. Seeing only implementation as innovation or the whole process of generation and implementation as innovation varies by study.

Innovation studies on creativity theory heavily focus on creativity, or generation of novel and useful ideas, assuming this eventually brings innovation to the organization, and theorize what drives the individual creativity that constitutes group and organizational creativity. First, individual characteristics such as personality, motivation, and emotion are considered the drivers of individual creativity. Eysenck (1993) argues that a trait of personality such as psychoticism, measured by unique responses on the word association, is a core of creativity, and creativity is related to genius. Grant and Berry (2011) argue that intrinsic motivation from desires to learn and curiosity is a driver of creativity, but primarily drives novelty, not necessarily usefulness. They show that prosocial motivation, or desire to help other people and produce beneficial outcomes, intensifies the relationship between intrinsic motivation and creativity, through perspective taking, or individuals' cognitive process of understanding others' values and needs, that develops usefulness as well as novelty. Self-leadership, generated by individual autonomy and generating self-motivation to perform well in an organization, also affects individual practice of creativity and innovation (DiLiello and Houghton, 2006). However, negative emotion is not necessarily undesirable, and may rather drive creativity. Zhou and George (2001) find that discontentment such as job dissatisfaction can encourage employees with high continuance commitment to change or improve their work situations and elicit creativity with helpful and supportive coworkers and high perceived organizational support for creativity. Furthermore, Fong (2006), seeing the co-existence of positive emotion such as excitement and happiness and

negative emotion such as frustration and sadness in an individual about the same event as an unusual emotion experience, argues that this emotional ambivalence increases individuals' sensitivity to unusual associations of things, which is important to organizational creativity.

Although individual characteristics are important to explain individual creativity, the contextual factors of their workgroup or workplace are also critical to help individuals express their creativity and generate group or organization-level creativity and innovation. Hülsheger et al. (2009), Page (2008) and West (2002) argue that diversity of knowledge and skills of group members determines creativity and innovation, evoking cognitive resource diversity more than background diversity such as age, gender, or ethnicity. Moreover, task and goal interdependence of group members stimulate communication and discussion to synthesize different viewpoints (Hülsheger et al., 2009). These group inputs of knowledge diversity, skills and interdependence generate innovation through the group process, which consists of vision, safe psychological atmosphere from trust and mutual support, group climate for excellence and strong cohesion (Hülsheger et al., 2009). Nijhof et al. (2002) study the role of shop-floor employees in innovation and suggest that exempting employees from their normal job when they come up with a promising idea and encouraging them to concentrate on the development and implementation, which builds an innovative climate, are critical to innovation. Organizational climate of management's belief in the potential and value of creativeness, low degree of formalization, employees' discretion, and open communication channels are considered critical to organizational creativity and innovation (Cummings, 1965; Nijhof et al., 2002). Martins and Terblanche (2003) also illustrate that organizational culture, defined as shared value, beliefs and expected behavior in an organization, influences creativity and innovation through socialization processes of learning acceptable behavior and activities and through enactment of basic values

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and beliefs in structure and management practice. Moreover, individual creativity is affected by information which individuals are exposed to in an organization, and thereby, organizational learning is an important determinant of individual creativity (Huber, 1998). Huber (1998) states that organizations learn through sensing changes in technology or competitor actions and from their ongoing experience and also others who already know.

However, since individual, group, organizational creativity and innovation are all intertwined, there are interaction perspectives on creativity and innovation. Oldham and Cummings (1996) propose an interaction effect of personal characteristics and organizational context, such that personal characteristics such as broad interest, attraction to complexity, institution, toleration of ambiguity and self-confidence interact with organizational context such as job complexity and supportive and noncontrolling supervision, and this interaction process affects employee creativity. Glynn (1996) reports that the interaction among members with different levels and types of individual intelligence (i.e., processing, interpreting, encoding and accessing information useful for task and environmental challenge) constitutes organizational intelligence, resulting in organizational innovation. Amabile (1983, 1996) argues that creative production requires domain-relevant skills (i.e., expertise), creativity-relevant skills including cognitive style and working style (i.e. creative thinking), and motivation by curiosity, enjoyment, or a personal sense of challenge, and a work environment for the individuals constituted by organizational motivation, resources, and management practice allowing freedom or autonomy (see also Andrews, 1976). She argues that creativity in general includes not only personal characteristics and cognitive abilities, but also social environments. Ford (1996) describes that individual creative behavior is conducted in organizational setting where sub-unit, group, organizational, institutional, and market domains are intertwined. He proposes the model that

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individuals build motivation to attempt future creative actions through sense making processes of seeking information and imposing meaning in information and elicit creativity with motivations combined with their knowledge and ability. Moreover, Woodman et al. (1993) suggest that organizational creativity, generated by individuals working in a complex social system, is a subset of a broader domain of innovation, which is also a subset of organizational change. His model shows that individual creative behavior --- as a function of cognitive ability, personality and biographical factors, relevant knowledge, motivation, and social and contextual influences --- influences organizational creativity interacting with group characteristics such as group composition, longevity, diversity, and cohesiveness. Lastly, a few studies probe the different effects of individual, group and organizational factors on generation of creative ideas and implementation as separate activities (Axtell et al., 2000; Baer, 2012). For example, Axtell et al. (2000) show in their study of shopfloor employees' innovation that suggestion of ideas rely on individual characteristics such as self-efficacy (i.e. confidence at performing proactive tasks) and role orientation (i.e. ownership of problems) more than group and organizational characteristics such as a participative and collaborative leadership and management style, whereas those group and organizational characteristics more strongly influence implementation of ideas. Baer (2012), focusing on the implementation stage, finds that not only employees' intrinsic motivation but also extrinsic motivation (e.g. monetary, career, and reputation benefits) is critical to implementation of ideas.

Thus, innovation studies on creativity theory see individual (e.g. personality, motivation, and emotion), group (e.g. composition, cohesion, and group management style) and organizational (e.g. goals, resources, leadership, management, and communication style)

variables and their interaction as drivers of innovation, or generation and implementation of a novel and useful idea.

2.2.3. Innovation and diffusion theory

Not only the generation of innovation, but also the diffusion of innovation has important implication for understanding the concept of innovation. The diffusion of innovation refers to the spread of innovation within a social system (Strang and Soule, 1998). For diffusion theorists, innovation is defined broadly as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption", for example, including new behavior, strategy, belief, technology, structure, laws, or policy, and innovativeness is determined by earliness of adopting new ideas by members of a social system (Berry and Berry, 1992; Gray, 1973; Rogers, 1995; Soule, 1999; Strang and Soule, 1998; Wejnert, 2002). Studies on diffusion of innovation usually focus on a particular innovation and explain how the innovation is adopted or diffused in terms of characteristics of innovation and innovators and environmental context, and using political, economic, and/or institutional perspectives (Gray, 1973; Rogers, 1995; Wejnert, 2002). The initial diffusion paradigm was established by Ryan and Gross'(1943) work about diffusion of hybrid corn among Iowa farmers. Seeing a diffusion process as a social process, they find that, while initial knowledge about the new seed is acquired by commercial channels such as salesmen, neighbors adopting the hybrid seed influence later acceptors, shortening the time for complete adoption. Although there is a different economic perspective to explain the lag in the development and entry of hybrids into different areas, following variants across localities in breeding superior corn and differences in the profitability of the shift to hybrids (Griliches, 1957), the perspective on social relation or contagion has still been important in the diffusion

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paradigm and has been broadened to apply to other areas of innovation (Valente and Rogers, 1995). Coleman et al. (1957) show in their diffusion study of a new drug, tetracycline called "gammanym," that the more profession-oriented doctors adopt the new drug earlier than the less profession-oriented ones and the doctors integrated in the network of friendships with their colleagues introduce the new drug into their practices faster than isolated doctors, although the difference is little at the very beginning, showing the effectiveness of network of interpersonal relations on the diffusion process. However, Burt (1987) argues in his diffusion study of tetracycline that the effect of social contagion on diffusion occurs through structural equivalence, not through cohesion, with physicians competing against each other to maintain their position in the social structure. Their joint occupancy of similar positions in the social structure triggers them to adopt a new drug in order to avoid embarrassment and maintain their reputation when diffusion reaches their status (Burt, 1987). Later, Van den Bulte and Lilien (2001) reanalyze earlier studies and argue that the effect of social contagion on diffusion of tetracycline is confounded with marketing effects measured by advertising volume because the drug is an un-dramatic innovation with little ambiguity and risk, making market effects dominant and information from earlier adopters less effective, once they control physician characteristics and seasonal effects. Explaining a policy adoption, Berry and Berry (1992) show that a state's adoption of tax innovation is affected by nearby states that have previously adopted it. However, Greve (1996) shows that the adoption of new firm strategies, such as a new radio format, is more strongly influenced by organizational change than social proximity to prior adopters. Radio stations do not require significant change in core technology for adopting new formats and firms are more likely to enter the new market due to low organizational inertia than through a corporate contact to other competitors (Greve, 1996). Thus, the social contagion perspective has

been used in diffusion studies, but often supplemented by other economic or strategic approaches.

Diffusion studies also focus on how the characteristics of innovations or innovators (i.e., adopters) affect the rate of adoption of innovations. Rogers (1995) characterizes innovation by their relative advantage, compatibility, complexity, trialability, and observability. Innovation that is perceived as advantageous by individuals, consistent with the existing values, easy to understand, and experiment with on a limited basis, and whose results are more visible can be adopted faster (Rogers, 1995). For example, preventive innovation such as health prevention requires action at one time, but its advantages are hard to perceive at the same time, thereby delaying adoptions of such innovations (Rogers, 2002). Zhu et al. (2006) analyze post-adoption of e-business using a synthesis of innovation characteristics (relative advantage and compatibility, and costs and security concerns tailored to the specificity of e-business innovation) and contexts of innovation (technology competence, organization size, competitive pressure, etc.). They find that compatibility of technology is the strongest driver of e-business usage; security concern is relatively stronger in inhibiting the usage than costs; and structural inertia may prevent large organizations from using the technology. Fliegel and Kivlin (1966) study the adoption of thirty-three farm practices in terms of costs, payoff, regularity of reward, and divisibility for trial and find that innovations with high divisibility for trials, high reward, and low risk are adopted rapidly. Brancheau and Wetherbe (1990), based on characteristics of adopters and their social relations, argue that uncertainty reduction behavior among potential adopters is important for diffusion of spreadsheet software in organizations. They show that earlier adopters of spreadsheet software are younger, more highly educated and often

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professional-level analysts and more engage in interpersonal communication, and interpersonal communication has a dominant effect in all stages of adoption.

As each study of diffusion usually deals with a particular innovation, many diffusion studies are independent and isolated using diverse or combined perspectives (Palmer et al., 1993; Walsh, 1993; Westphal et al., 1997). Walsh (1993) develops a model of innovation including technological, environmental and political factors to analyze the various innovations in the retail food industry, such as frozen meat, boxed meat, scanner and computerized ordering machine, and explains the adoption of those innovations in supermarkets. He argues that political contingencies (e.g., centrality, substitutability, coping with uncertainty) and market context (e.g., technology, product characteristics, environmental uncertainty and munificence, etc.) affect innovation outcomes through change of the social relations among managers, workers, consumers, suppliers and the state in the system. For example, the implementation of the scanners was delayed because of the need for complex cooperation among retailers, food manufacturers and computer companies, and resistance by workers whose core tasks are attacked and customers who suffer from inconvenience from price removal, while the computerized ordering machine was adopted quickly, because it expanded worker skills, automated a routine task, and facilitated the decentralization of ordering responsibilities at a time of increasing store size (Walsh, 1993). Palmer et al. (1993) examine which among economic, political and institutional factors can best explain the adoption of the multidivisional form among large US corporations, and find that institutional factors such as coercive pressures of capital-dependent corporations, normative pressures of being legitimate and reliable information through non-directional ties have a dominant effect on adoption of the multidivisional form over political factors, but complemented by the effect of economic factors of cost reduction. Westphal et al.

(1997), in their study of adoption of total quality management (TQM) practices among hospitals, focus on the difference between early adopters and later adopters. They argue that earlier adopters explore or customize specific TQM practices suitable to their organizational capabilities and resources under the limited institutional forces while later adopters simply conform to the normative form of TQM through network ties. In addition to these sociological perspectives, some diffusion studies are grounded in an economic perspective (Audretsch and Feldman, 1996; Baptista, 2001; Cockburn et al., 1999; Jaffe et al., 1993; Mansfield, 1961). For example, Mansfield (1961) analyzes the spread of twelve innovations in four industries: bituminous coal, iron and steel, brewing and railroads, and finds that imitation of new techniques gets faster when innovations are more profitable and require small investment, and in more competitive industries. Also, based on economic geography, the diffusion of knowledge is spatial and influenced by distance from the knowledge source, the level of geographical concentration in industries, and networks between adopters and potential adopter and between producers and users of new knowledge (Audretsch and Feldman, 1996; Baptista, 2001; Jaffe et al., 1993).

Thus, although diffusion studies are mostly independent focusing on particular innovations and defining innovation broadly as a new idea or practice including new behavior, strategy, belief, technology, structure, laws and policy, the actual meaning of innovation in diffusion theory is *societal adoption of a new idea*, not simply a new idea itself. Generally, one thinks innovation is improvement. However, based on diffusion theory, innovation does not have to be improvement. A simply new idea, which is not always an improved one, can be diffused. For example, the tactic of sit-out, camp-outs, and sleep-in was spread to student activists of the shantytown in 1970s and 1980s because it was compatible with students' experiences and beliefs without carefully examining the effectiveness of the tactic, and consequently was not successful,

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not achieving its goal (Soule, 1999). Also, as discussed in Rogers' (2002) preventive innovation, its consequence may not be observed at the time of adoption so that it can turn out to be either a success or a failure. For example, Westphal et al. (1997) show that late adopters of TQM gain little performance benefits from the innovation. Therefore, innovation on diffusion theory refers to societal adoption of any new idea or practice, which could be effective or ineffective, and this adoption is affected by characteristics of the new practice and adopters, and contextual --- economic, political, institutional, or social --- factors.

2.2.4. Innovation as a continuous or discontinuous concept

Schumpeter (1939) distinguishes innovation --- any "doing thing differently" in the economic life --- from invention, and addressed that "the making of the invention" and "the carrying out of the corresponding innovation" are different. Innovation can occur without invention, and invention does not necessarily lead to innovation (Schumpeter, 1939). However, Solo (1951), defining inventions as "changes in the knowledge available" and innovations as "changes in the actual technological arrangements of existing knowledge applied" both included in technological change, argues that invention and innovation are considered an ordinary business activity both subject to cost and revenues, not distinct activities with one as a business activity and the other placed outside the economic activity. Ruttan (1959) points out that Schumpeter and growth theorists, whose main interest is changes in production function by technological change, pay little attention to the process by which innovation is generated. He sees innovation as any "new thing" in science, technology, or art, and invention as a subset of technical innovation that is patentable. Moreover, he argues that the distinction between invention and innovation has no real conceptual basis, and there may be more advantages by eliminating this distinction and instead

creating precision by dividing innovation into "scientific innovation," "technical innovation," or "organizational innovation" (Ruttan, 1959). Making the distinction between invention and innovation becomes more difficult as we try to understand inventive activity as a continuing activity and the process of invention proceeding to full commercial application (Rosenberg, 1975). Rosenberg (1975) argues that the lengths of the lag between invention and full commercial exploitation vary by industry and also by complexity of the technical problem and the degree of establishing economic superiority over existing techniques, and innovation is linked to the inventive process. This discussion is also related to the conceptualization between creativity and innovation. If we characterize innovation as a broad concept including creativity in multistage processes requiring multilevel interactions, not a limited concept to implementation of ideas, innovation should be considered a relatively more continuous process (Baer, 2012; Ford, 1996). Furthermore, the diffusion process of innovation proceeds through a series of improvements, modifications and adaptations of practices to the specialized requirements of various submarkets, implying that innovation is not a clearly defined single act (Rosenberg, 1975). Westphal et al. (1997) point out that while some innovations are discrete, others can be open to interpretation and vary in form so that exploring different definition and implementation of an innovation is more important than simply predicting adoption or not. Robertson (1967) shows that innovation is neither totally an accidental affair nor a mechanistic affair, rather being a cumulative synthesis of familiar elements and novel elements, and classifies innovation as continuous innovations (e.g., fluoride toothpaste, new-model automobile change-overs), dynamically continuous innovations (e.g., electric toothbrushes, Touch-Tone telephones) and discontinuous innovations (e.g., television, computers). Rogers (1995) also introduces the concept of technology cluster due to the difficulty of determining boundaries around

technological innovation, i.e., where one innovation stops and another begins, and argues that the perception of newness and the boundary between innovations are determined by potential adopters. Stinchcombe (1990) argues turning inventions into innovations is difficult because the information and decision system required for inventions and associated with inventors, is different from that for innovations, which is more associated with managers. Furthermore, turning invention to innovation for producing monopolistic advantage involves creating a social system to maintain the advantages of the learning curve and network connections between innovators and their clients, and arranging for the division of benefits between investors and personnel (Stinchcombe, 1990), implying that it is hard to define innovation as a single act in this process of building a social system.

Accordingly, the concept of innovation and the drivers of innovation vary by theoretical background and there is no consensus covering all theories. Innovation studies based in one theory see one side of innovation, but are less aware of the other sides. Understanding these different perspectives on innovation studies is a starting point to conceptualizing innovation at a higher level, potentially encapsulating all those streams. This discussion suggests the need for further work on the fundamental meaning of innovation, grounded in the philosophy of technology and innovation. This review suggests a starting point for such a project.

2.3. Conclusion

Innovation studies generally gloss over how innovation has been discussed in different contexts, simply employing a working definition. This chapter examines the meaning of innovation in various theoretical perspectives: growth theory, creativity theory, and diffusion theory to show

innovation can be defined differently and how multi-disciplinary or interdisciplinary innovation

research could be.

CHAPTER 3

EVALUATING AND EXTENDING INNOVATION INDICATORS FOR INNOVATION POLICY

3.1. Introduction

Innovation is a key but poorly understood concept in management, economics, sociology and public policy. While innovation is widely seen as a key to economic growth and improved well-being, the uses and the measures of the concept vary across studies. Starting from the early work of Schumpeter (1939, 2008), one can see a variety of uses of the term "innovation" in the literature, and also a proliferation of measures even among those who share underlying concepts. This suggests a need to map and clarify the uses of the term "innovation" and its various indicators, in order to facilitate innovation studies that are focusing on the drivers and outcomes of something called "innovation." This chapter shows the variety of operationalizations that are commonly used based on the Schumpeterian perspective. Then, based on a variety of data sources including NSF, CIS (German data only), USPTO and multiple original US survey data, this chapter shows how the different measures co-vary, and what underlying aspects of the innovation concept they seem best to capture. Innovation has been measured by public and private surveys or patents, and each measure has been used for independent studies with some advantages and disadvantages. However, there is a need to cross-validate different measures of innovation indicators. This study tries to achieve this goal. Moreover, the process of cross-validation of measures created by different data sources opens the discussion about difficulties in linking innovation concepts (e.g. what is innovation, or trivial vs. blockbuster innovation) and measures, and further brings us to a more comprehensive view on innovation including

innovation from outside of R&D activity as well as innovation from R&D activity. This introduces the concept of non-R&D innovation. We develop measures of non-R&D innovation using original US surveys, which highlight some of the limitations of many current measures and conceptualizations and add new statistics to those by public surveys, to both develop and clarify the concept of innovation and also help improve the concept as it might be used in science, technology and innovation management and policy. Finally, the challenge of measuring R&D and non-R&D innovation is discussed, which needs to be considered to create better innovation indicators. Overall, the results contribute to conceptualizing innovation, cross-validating innovation indicators created from different data sources, developing science and innovation indicators beyond the R&D-based perspective in innovation policy, and emphasizing the importance of understanding the broad universe of innovative activity.

3.2. Conceptualizing innovation

According to the Oslo manual (OECD, 2005), an innovation is defined as "*the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations...* The minimum requirement for an innovation is that the product, process, marketing method or organisational method must be *new (or significantly improved) to the firm.*" Many innovation studies have used slight modifications of this definition as their starting point. Although innovation can be defined and interpreted differently by scholars, their common starting point is Schumpeter. Schumpeter (2008) argues that the engine of capitalism is production for the mass market and this engine is kept in motion by creative destruction, i.e., the continuous process of generating new products, processes, markets and organizational forms that

make existing ones obsolete. Thus, for Schumpeter, innovation is the setting up of a new production function through the process of creative destruction (Schumpeter, 1939). Creating new ways of production, as well as new products, is an important driver of economic growth. Rosenberg (2004) shows that increasing inputs accounts for a small portion of the actual growth (about 15%) and the rest of growth comes from creating new ways to produce more output from the same amount of inputs. Although Schumpeter (2008)'s concept of innovation covers more broadly including organizational change in the process of creative destruction, innovation has been often discussed in terms of the technological change causing economic growth. Thus, the meaning of innovation in the Schumpeterian perspective is *technological change that yields more or better output from a given bundle of inputs* (Mansfield, 1972; Romer, 1986, 1990, 1994). In this conceptualization, the term innovation is often equated with technological innovation. This study uses this conceptualization.

3.3. Measurement of innovation

Innovation policymakers have struggled with the problem of how to develop innovation indicators that capture innovative activity in the contemporary US economy (NRC, 2014). Many innovation studies use specific types of innovation to narrow their focus or to consider diverse dimensions or characteristics of innovation, such as technological innovation including product and process innovation, exploratory or exploitative innovation (Greve, 2007; Jansen et al., 2006), incremental or radical innovation, disruptive innovation (Govindarajan and Kopalle, 2006), architectural innovation (Henderson and Clark, 1990), and user innovation (von Hippel, 2005). Service innovation is hard to define, and has been usually included in product innovation (OECD, 2005). Recently, innovation surveys try to measure organizational innovation, in

addition to the more traditional product and process innovation. The following section, focusing on technological innovation, discusses common measures of innovation which are heavily used by innovation studies in the Schumpeterian perspective, compares them, and examines the link between the concepts of innovation and those commonly used measures.

3.3.1. Innovation indicators

Innovation studies have generally used R&D, patents, or survey-based measures as innovation indicators. First, R&D expenditure or intensity measures innovative effort, which is either used as a dependent variable to explain the relationship between firm size and innovative effort (Cohen, 2010) or an input to innovation (Kemp and Pearson, 2007; Romer, 1986, 1994). For decades, R&D has been treated as equivalent to innovation. Consistent with this view, from 1953 to 2007, the US National Science Foundation (NSF) managed the Survey of Industrial R&D, collecting information about R&D performing firms, not separately measuring innovation distinct from doing R&D. Although R&D is a good proxy for technological progress because it is an intended activity directed toward innovation, it has limitations as a good proxy because technology can progress without much R&D and R&D-related indicators do not include innovation outside organized R&D, for example, through learning by doing, tooling and construction, manufacturing and marketing activities (Mansfield, 1972; Mukhopadhyay, 1985). Only in 2008 did NSF begin to collect additional indicators of innovation such as patents or commercialization of new products or processes. Geroski (1990) points out that R&D expenditures are a poor measure of true research activity, underestimating the research activity of small firms in competitive industries. Blundell et al. (1999) and Klette and Kortum (2004) also argue that R&D is often allocated in an arbitrary manner in firm accounts and not even reported

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by many firms, and R&D intensity has a highly skewed distribution. Thus, R&D cannot be simply equated with innovation, and rather has to be considered one input for innovation.

In addition to R&D, patent-based indicators have been commonly used as an innovation output measure (Cohen, 2010; Jaffe et al., 1993). Patents have the benefits of public availability of the data and of being an unobtrusive measure. However, a patent cannot be equated with innovation because not all innovations are patented (Blundell et al., 1999). Firms have different strategic reasons for patenting and also use other appropriability mechanisms such as secrecy, lead time and long-period contracts, for protecting inventions with different values or depending on the difficulty of codifying inductive and empirical knowledge (Anton and Yao, 2004; Arora, 1997; Arundel, 2001; Cohen et al., 2000; Hall et al., 2012). Even for inventions registered at the USPTO, the majority of those are never commercialized (Kline and Rosenberg, 1986), and, furthermore, one innovation may involve many patents (Cohen et al., 2002). Thus, the problems of R&D not being a clear substitute for a measure of innovation, especially for evaluating the efficiency of government funds, and the problem of an increase in patents not reflecting an increase in innovation highlight the need for a measure of innovation that allows a direct link between innovation outcomes and relevant policy variables (NRC, 2014). Moreover, Arora et al. (2014) show that for about half of innovations in the US, sources of invention and locations of innovation are not the same. The invention moves during the commercialization process and this also requires a separate measure of innovation from R&D and patents.

Consistent with this demand, alternative innovation measures are collected by surveys or counting innovations to consider all innovations regardless of R&D and patenting. There have been private and public innovation surveys to directly measure innovation in European and North America over the years, for example, the Community Innovation Survey (CIS) in Europe

(1993 - present), NSF's Business R&D and Innovation Survey (BRDIS) in the US (2008 -

present), and private surveys such as the US Division of Innovative Labor Survey (DoIL) (Arora

et al., 2014), as well as a sequence of Canadian Survey of Innovation and Business Strategy

(1993 - present) and old innovation surveys done in Italy, France and Nordic countries before the

initiation of CIS (Gault, 2013; Gerstein et al., 2004). Although some of these surveys use slight

variations, most build on the OECD definition of innovation. The measures depend on

respondents' interpretations of innovation, and novelty and improvement of products and

processes embedding socio-economic benefits, complementing limitations of patent measures

(Tremblay et al., 2010). Although less commonly used than survey-based measures, counts of

innovations identified through expert appraisal as those by SPRU, University of Sussex for major

innovations in the UK, 1945 – 1983 (Blundell et al., 1999; Geroski and Pomroy, 1990) or counts

of new product announcements in trade journals and magazines (Coombs et al., 1996; Fosfuri

and Giarratana, 2009) have been also used as measures of innovation. For example,

pharmaceutical innovations are measured by clinical trials, counts of drug products, journal

articles, or the number of new molecular entities (Dubois et al., 2011). Counting new product

announcements in technical and trade journals allows collecting information about companies'

innovation productivity and innovations timed close to commercialization, although they may

rarely cover process innovations, and may have selection biases from choice of journals by

researchers and new product selection by the journal editors (Coombs et al., 1996; Kemp and

Pearson, 2007; Tidd, 2001). Finally, some have used historical records from World's Fairs and

similar exhibitions of new technology to track innovation counts (Moser, 2005). For this study,

the focus is on innovation-relevant measures from patent database, public and private surveys,

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mostly related to product and/or process innovation. Sections 3.3.2 and 3.3.3 will compare these indicators and discuss ties among indicators and concepts.

3.3.2. Comparison of measures

In this section, different innovation-related indicators are created from different data sources. First, R&D data are collected from NSF's Industrial R&D Survey (NSF, 2011), NSF's BRDIS (NSF, 2013) and the US DoIL Survey (Arora et al., 2014), a private innovation survey. Second, patent-related data are collected from the USPTO through the NBER database (Hall et al., 2001) and the US Inventor Survey (Walsh and Nagaoka, 2009), a private survey of triadic patents, as well as NSF's BRDIS.   Lastly, survey-based innovation indicators are created from CIS German data (Aschhoff et al., 2013), NSF's BRDIS and DoIL. The datasets are described in Table 3.1.

Table 3.1. Different data on innovation

Survey (Ownership)		Year covered	Respondent (Response rate)	Description
R&D-focused survey	Survey of Industrial R&D 2007 (NSF)	2007	Representatives at for-profit R&D-performing companies (80%)	The survey collects information about amount of R&D expenditure, sources of funding, character of R&D work, R&D employees, and company performance and basic profiles.
Patent-focused survey	US Inventor Survey (Private)	2000 to 2003	Inventor on triadic patent (32%)	The survey is sampled from US inventors on triadic patents (patents filed in Japan and the EPO and granted by the USPTO). The data include inventors' education, employment and motivations, invention process, and use of invention and the patent.
Innovation survey	BRDIS 2008 (NSF)	2006 to 2008	Persons familiar with topical areas of the survey in the US (parent) company with 10+ employees (77%)	The survey includes companies' financial information, R&D activities, human resources, intellectual property, and innovation during 2006 to 2008.
	DoIL (Private)	2007 to 2009	Marketing manager or another person in the business unit familiar with its products and services (30%)	The survey is sampled from firms in US manufacturing and selected business service industries, and include information about sources of invention and channels through which the division of innovative labor functions for innovation during 2007 to 2009.
	CIS 2010 (Eurostat)	2008 to 2010	Enterprises with 10+ employees (DE-23%)	The survey collects information about innovation activities of enterprises in European countries, and the sources and barriers of innovation activities including organizational and marketing innovation.

Notes:

All NSF surveys' response rates are provided by the NSF NCSES Surveys page.

CIS 2010-DE response rate is from the Community Innovation Survey 2010 Synthesis Quality Report by European Commission.

Comparison is done at the industry level due to limitations on accessing micro-level data for the surveys and also to allow creation of concordances across data. Tables 3.2 and 3.3 present the measurement of and comparison among different indicators of innovation for organizations (e.g. business units in DoIL, parent firms in NSF's surveys, and enterprises in CIS) with 10+ employees from different data sources by manufacturing industry, using 2007 NAICS categories. To compare industries, a concordance between US patent class and NAICS published by the USPTO and a concordance between NAICS and NACE published by the US Census are used. R&D-based measures are R&D intensity (i.e., industry R&D expenditure divided by industry sales, column 1 in Table 3.3) and the percentage of R&D performers in each industry (columns 2 and 3 in Table 3.3) from two different sources: NSF and DoIL. Patent-based measures are the number of patent applications from each industry divided by industry sales (column 4 in Table 3.3), the number of patents granted to each industry divided by industry sales (columns 5 in Table 3.3), and the number of patents classified into the product industry divided by industry sales (column 6 in Table 3.3). Columns 7 to 11 in Table 3.3 present the rates of innovators by industry from BRDIS, DoIL, and CIS (Germany). Such indicators are related, but distinct, and are often used together in a given study. Therefore, comparing different innovation indicators and also those from different data sources helps calibrate and validate each measure to others and understand the extent to which they capture the same concept (Blalock, 1968).

Table 3.2. Indicators and measures at the industry level

Indicator	Data source	Measure
R&D Intensity	BRDIS 2008	$\dfrac{\text{Expense for domestic R\&D performed by the companies}}{\text{Domestic sales}}$
R&D performers	NSF 2007 Survey of Industrial R&D	% of companies spending more than zero expense for R&D
R&D performers	DoIL 2010	% of firms saying yes to the question "Does your company conduct R&D?"
Patent applications	BRDIS 2008	$\dfrac{\text{\# of US patent applications}}{\text{Domestic sales}}$
Patents	BRDIS 2008	$\dfrac{\text{\# of US patents issued}}{\text{Domestic sales}}$
Patents	NBER (Patents issued in 2006) BRDIS 2008 (domestic sales)	$\dfrac{\text{\# of any US patents related to the product industry}}{\text{Domestic sales}}$
New-to-Firm product innovator	BRDIS 2009	% of companies that introduced new or significantly improved goods or services
New-to-Firm product innovator	DoIL 2010	% of firms that introduced new or significantly improved goods or services to the firm
New-to-Firm product innovator	CIS 2010 (Germany)	$\% \dfrac{[\textbf{Product} \text{ innovative enterprises only}]+ [\textbf{Product} \text{ and process innovative enterprises only}]}{\text{\# of total enterprises}}$
New-to-Market product innovator	DoIL 2010	% of firms that introduced new or significantly improved goods or services to the industry
New-to-Market product innovator	CIS 2010 (Germany)	% of enterprises that introduced a new or significantly improved good or service onto your market before your competitors

Notes:

BRDIS domestic sales data are representative of companies where (worldwide R&D expense+ worldwide R&D cost funded by others) > 0.

New-to-firm product innovators in CIS here are defined as firms that introduced any product innovation, which is a union of "product innovative enterprises only" and "product AND process innovative enterprises only". Data are from Eurostat.

Table 3.3. Comparison of indicators

Indicator	(1) RDI (R&D exp /Sales) %	(2) RDP (% of R&D performers)	(3) RDP (% of R&D performers)	(4) Patent app (# of pat app /Sales ($bil))	(5) Patent (# of pat grant /Sales ($bil))	(6) Patent (# of pat grant /Sales ($bil))	(7) NTF Inno (% of NTF innovators)	(8) NTF Inno (% of NTF innovators)	(9) NTF Inno (% of NTF innovators)	(10) NTM Inno (% of NTM innovators)	(11) NTM Inno (% of NTM innovators)
Source	BRDIS 2008	NSF RD-1	DoIL	BRDIS 2008	BRDIS 2008	NBER	BRDIS 2009	DoIL	CIS 2010-DE	DoIL	CIS 2010-DE
NAICS / Period	2008	2007	07 to 09	2008	2008	2006	07 to 09	07 to 09	08 to 10	07 to 09	08 to 10
311 Food manufacturing	0.4	7.2	22.9	0.9	0.3	0.6	19.5	39.2	36.6	12.9	9.3
312 Beverage and tobacco product manufacturing	0.6	2.7	27.7	3.9	1.6	0.9	21.9	42.9	52.4	18.1	26.5
313-6 Texitle, apparel and leather	0.6	4.1	21.3	4.4	2.0	8.8	19.4	36.8	53.9	15.2	22.6
321 Wood product manufacturing	0.7	1.9	11.9	3.5	1.5	5.3	9.0	20.8	48.8	7.5	10.9
322-3 Paper manufacturing, printing and related support activities	1.3	4.9	13.7	10.6	6.3	4.7	20.7	39.5	47.3	8.6	14.8
324 Petroleum and coal products manufacturing	n.a	**34.3**	31.5	2.8	1.4	n.a	13.6	29.6	52.5	18.8	9.8
325 Chemical manufacturing (except pharmaceutical and medicines)	1.9	**32.4**	**54.6**	17.6	7.0	21.5	**37.9**	**51.9**	**79.2**	**25.0**	**49.4**
3254 Pharmaceutical and medicine manufacturing	**12.2**	**89.8**	**69.2**	22.8	9.7	14.3	**32.2**	**61.8**	**71.7**	**30.4**	**40.6**
326 Plastics and rubber products manufacturing	1.1	16.4	30.8	9.5	7.3	23.6	27.2	47.4	54.7	16.6	29.6
327 Nonmetallic mineral product manufacturing	1.9	6.3	16.1	16.0	6.3	23.1	18.3	29.5	50.7	9.0	31.4
331 Primary metal manufacturing	0.4	11.4	19.3	1.7	0.7	3.4	12.1	38.1	35.8	9.2	26.8
332 Fabricated metal product manufacturing	1.6	5.4	18.8	14.6	4.3	**50.7**	14.0	37.8	31.1	10.0	14.0
333 Machinery manufacturing	**3.5**	18.6	37.4	**23.6**	**12.9**	**78.8**	26.8	44.7	66.0	21.0	34.5
334 Computer and electronic products	**10.1**	**41.3**	**53.2**	**78.1**	**42.3**	**167.9**	**48.5**	**64.5**	**78.8**	**32.6**	**42.9**
335 Electrical equipment, appliance, and component manufacturing	**2.7**	**24.9**	**43.5**	**36.7**	**19.4**	**118.9**	**37.5**	**56.2**	**70.9**	**28.2**	**40.1**
336 Transportation equipment manufacturing	**2.6**	20.3	**38.2**	9.7	5.5	8.6	**30.7**	49.6	**70.0**	27.9	34.8
337 Furniture and related product manufacturing	1.4	4.6	16.5	**24.0**	**13.1**	18.6	14.4	40.8	45.6	13.7	16.8
339 Miscellaneous manufacturing	n.a	15.4	36.7	**33.0**	**13.7**	**43.6**	29.9	**54.9**	59.2	23.8	25.1
All	3.5	12.1	27.1	20.3	10.2	37.1	23.1	42.5	50.2	15.9	23.2

Notes:

Bold numbers indicate top 5 industries in each indicator.

Col (6) - NAICS was assigned to each patent on its product industry using the USPTO concordance between the U.S. Patent Classification System and NAICS. New to firm innovators include new to market innovators by definition.

For German data, NAICS-NACE concordance was applied. For the grand means of manufacturing (All) in Germany, only manufacturing industries covered by concordance were used.

Col (8) and (10) from the DoIL data show the percent "yes" from the questions asking if the firm has a new to firm [NTF] or new to market [NTM] innovation. However, DoIL has additional questions asking what percent of revenue is from the innovation (for both new to firm and new to market innovation) and in which year they introduce the innovation (only for new to market innovation). Some responses show zero percent of revenue and/or introduction outside 2007-2009 time window, both of which do not match the operational definition: "any new or significantly improved goods or services (to your firm/to your industry before any other company) earning revenue" between 2007 and 2009. Therefore, we excluded those erroneous responses, including only clean responses in col (8) and (9). Before this cleaning, the share of NTF was 43.2% and NTM was 18.3%.

Table 3.4. Correlations and factor analysis

	Indicator	Source	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Factor 1	Factor 2
(1)	**RDI**	BRDIS 2009	1.00										0.73	0.40
(2)	**RDP**	RD-1 2007	**0.90**	1.00									0.90	0.10
(3)	**RDP**	DoIL	**0.79**	**0.88**	1.00								0.96	0.22
(4)	**Patent app**	BRDIS 2008	**0.69**	0.39	**0.53**	1.00							0.35	0.92
(5)	**Patent**	BRDIS 2008	**0.66**	0.36	**0.50**	**0.99**	1.00						0.32	0.94
(6)	**Patent**	NBER	**0.50**	0.28	0.44	**0.90**	**0.91**	1.00					0.22	0.91
(7)	**NTF Inno**	BRDIS 2009	**0.64**	**0.55**	**0.82**	**0.76**	**0.76**	**0.68**	1.00				0.76	0.55
(8)	**NTF Inno**	DoIL	**0.73**	**0.63**	**0.84**	**0.70**	**0.68**	**0.56**	**0.90**	1.00			0.82	0.43
(9)	**NTF Inno**	CIS 2010-DE	**0.61**	**0.62**	**0.83**	**0.59**	**0.60**	**0.50**	**0.87**	**0.70**	1.00		0.81	0.37
(10)	**NTM Inno**	DoIL	**0.72**	**0.72**	**0.92**	**0.64**	**0.63**	**0.57**	**0.88**	**0.87**	**0.88**	1.00	0.86	0.40
(11)	**NTM Inno**	CIS 2010-DE	**0.56**	**0.55**	**0.78**	**0.54**	**0.53**	0.48	**0.83**	**0.74**	**0.83**	**0.74**	0.80	0.31

Note: All bold numbers are significant at .05 level.

Comparing across indicators, Table 3.3 shows that the top 5 industries are very similar within each group of indicators of R&D, patent, and innovation. For R&D-based indicators, the total percentage of R&D performers from the NSF Survey of Industrial Research and Development (RD-1) in column 2 and that from the DoIL data in column 3 are somewhat different (12.1% v. 27.1%). There could be several reasons. First, the RD-1 shows 2007 data while, because of the skip logic, DoIL asked for R&D activity related to innovation during 2007 to 2009 only for new to market innovators. If their new to market innovation is not from R&D, they are asked if they conduct R&D at the time of phone survey (i.e., in 2010). For non-innovators and new to firm innovators, R&D data were updated by further search (e.g., follow-up phone calls, company websites, Hoover's reports, etc.) after the survey). For non-innovators and new to firm innovators, R&D data are updated by further search (e.g., follow-up phone calls, company websites, Hoover's reports, etc.) after the survey. Second, NSF's R&D performers are companies which spend R&D expense greater than zero. On the other hand, DoIL asks the sales or business manager if the business unit conducts R&D, which is a more simplified way to ask about R&D activity so that respondents might more readily include informal R&D as well as formal R&D

activity, and may allow us to find more small and medium size firms conducting R&D (Kleinknecht et al., 2002). Those reasons may affect the indicator's mean level. However, the percentages of R&D performers in those two datasets present similar patterns across industries. In particular, 4 out of 5 most innovative industries in columns 2 and 3 are the same industries (i.e., NACIS 325 Chemical, NAICS 3254 Pharmaceutical, NAICS 334 Computer, and NAICS 335 Electrical). Also, the rates of R&D performers are highly correlated across the two surveys (r = .88), as shown in Table 3.4.

For patent-based indicators, patent applications in column 4 and patents in column 5 are from the responding companies in BRDIS 2008, which uses industry information on firms that applied for or were granted patents, while patents in column 6 are from the USPTO, classified by product industries, based on a concordance between patent class and product industry. In other words, patents used in column 6 are produced by firms regardless of industry and then classified into product fields.[1] Although these three patent-based measures show somewhat different aspects of patenting (i.e. patent applications by assignee firms, patents granted to assignee firms, patents in relevant product industries), they all show machinery (NAICS 333), computer and electronic products (NAICS 334) and electrical equipment, appliance, and component (NAICS 335) are the most innovative industries in terms of patents. Columns 7 to 11 compare (product) innovator indicators from three different innovation surveys. The percentage of overall new to firm innovators in DoIL (42.5%) and the percentage in CIS 2010 German data (50.2%) are distinctly different from the percentage of overall new to firm innovators in BRDIS 2009

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[1] Patents can be assigned to parent companies or holding companies which are not actual business units producing those inventions. Therefore, using a product industry rather than the assignee's industry can better reflect the industry closely related to the business unit.

(23.1%). It may be hard to match numbers across surveys due to unobserved errors possibly from different survey questionnaires, length, target respondents, methods and so on. In particular, such survey comparisons are sensitive to industry and firm size composition and the weightings used. However, the pattern of industries across indicators is consistent, with high correlations (.70 to .90) among those indicators in the three innovation surveys (Table 3.4). The top 5 most innovative manufacturing industries are the same across the different innovation surveys except for one industry in DoIL (column 8 in Table 3.3). Based on the result of comprehensive comparison among all indicators in Table 3.3, we can see that computer and electronic products (NAICS 334), and electrical equipment (NAICS 335) are highly innovative industries according to all indicators, while chemical (NAICS 325) and pharmaceutical (NAICS 3254) manufacturing are included in highly innovative industries only for the indicators of R&D and innovation, not for the patent indicators. Cohen et al. (2002) show that discrete product technologies (e.g. food, chemicals, drugs, metals, and metal products) consist of one or a few patentable elements while complex product technologies (e.g. machinery, computers, electrical equipment, instruments, and transportation equipment) are composed of a large number of separately patentable elements including essential complementary components of the technologies (resulting in more patents per innovative product). Furthermore, in industries using complex technologies, patents are less used for enforcing exclusivity and more for negotiation in mutual dependence with others' patents than in industries using discrete technologies, leading to stockpiling uncommercialized patents (Cohen et al., 2002). This may explain why chemicals (NAICS 325) and pharmaceuticals (NAICS 3254) are in the top 5 most innovative industries in terms of R&D and innovation measures, but not patent-based measures.

The different indicators are highly correlated with each other, as shown in Table 3.4, which is the reason why those indicators are commonly used for innovation studies. However, the correlations above do not mean those indicators are substitutable for each other. The factor analysis in Table 3.4 finds that patents are distinguished from other indicators while R&D and innovation share a common factor. A factor including both R&D and innovation is consistent with many innovation studies, which use R&D as a proxy for innovation. However, R&D does not mean the generation and implementation of new ideas, but rather is one input for creating a new idea or facilitating its adoption. Moreover, the correlation sizes between R&D and innovation indicate a close relation between the two, but also unexplained variation in innovation, suggesting the possibility of activities outside R&D leading to innovation (especially for new to firm innovation, which tends to have a lower correlation with R&D measures than new to market innovation). This will be discussed more in section 3.4. Since interpreting innovation measures, especially from surveys, is also not straightforward, we need further discussion about what the measures mean.

3.3.3. Difficulties in linking innovation concepts and measures

The product innovation measure used by most current innovation surveys is premised on a perspective based on Schumpeter (1939, 2008), Solow (1956) and Romer (1986, 1990), which sees innovation as a driver of economic growth. BRDIS uses the question "did your company introduce any of the following (e.g., new or significantly improved goods, new or significantly improved services, etc.) during the three-year period, 2007 to 2009?", and DoIL uses the question "in 2009, have you earned revenue from any new or significantly improved goods or services in your industry introduced since 2007, where "new" means new to your firm?". These

innovation surveys often distinguish new to market innovation from new to firm innovation. If innovation means technical change producing more or better output from a given bundle of inputs, the distinction may not be that critical as long as it contributes to growth. On the other hand, if the level of novelty among innovations needs to be considered, the distinction may be useful. They can also show different innovativeness based on diffusion, which sees innovation as societal adoption of new ideas. For example, new to market innovation may be seen as invention and new to firm (but not market) innovation may be seen as adoption or imitation (although one cannot trace the diffusion of specific innovations using this measure). Furthermore, it is important to note that economically important innovations may not be equated with high sophistication or novelty of technologies, but rather can often be derived from well-known or trivial technologies (Kline and Rosenberg, 1986). This makes it hard to define what is a trivial innovation and what is a blockbuster innovation. Some may point out that most innovations are trivial because mostly they are modest technological improvements (annual updates to automobiles or smartphones, for example), or are variations on a theme (for example, so-called "me-too drugs"). Others may argue that a given innovation is a blockbuster because it creates high revenue, while others may focus on the technological advance embedded in the innovation when deciding if it is a trivial versus blockbuster innovation. Thus, when discussing trivial and blockbuster innovations, inconsistent standards are often applied. While some innovations are trivial based on technology, they may be important based on revenue (the Post-It note may be the canonical example).

Moreover, a new or significantly improved product or service which does not create revenues at the time of measuring, although it has potential commercial benefits, can be excluded from a measure of innovation when using surveys. It is not clear whether we see this as

invention, innovation, or something else because it can be a new idea at the stage of implementation, but other conditions such as regulation and market demand do not allow the new technology or product to enter the market. Similarly, firms can create their markets, in part by modifying the regulatory environment, turning a potentially failed invention into a major innovation (without changing its technological characteristics). For example, new drugs cannot be commercialized without FDA approval, which may be becoming a more political process now affected by patients' demand and their lobbies. Therefore, pharmaceutical firms foster and subsidize patient advocacy groups and create alliances with them for media press to get their new drugs approved, which creates their market (Carpenter, 2004). Another example comes from an interview with US inventors working in a specialty chemical company.[2] They told how they changed their business environment to facilitate commercializing their newly-invented greener chemical in a market where a competitor's product was dominating. They worked with Japan and environmental groups such as World Wildlife Fund (WWF) to lobby the US government to join an international treaty banning existing toxic chemicals (produced by their competitors), creating a demand by coating companies for their new product. Their IP on the new greener chemical had no value before changing the business environment. Now, the changed environment opened up the new market and enabled them to make profits from this new solution.

Therefore, the conceptualization of a commercially feasible product from an invention requires the cumulative process of practice and solving complex technical and social problems (Rosenberg, 1975). Furthermore, the economic profitability of invention is different from

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[2] Inventor survey follow-up interview, conducted August 9th, 2012. As part of the inventor survey, we interviewed several inventors to gain more details about the invention process that led to their triadically patented invention. We also interviewed additional inventors and managers about other non-R&D inventions.

establishing technical feasibility for an initial conceptualization of a product and requires the cumulative modifications of performance in economic terms and establishment of economic superiority over an existing product, sometimes through changing the institutional environment (Rosenberg, 1975). However, even after establishing the technical and economic feasibility, innovation may not be profitable if solid network connections between an innovator and its clients are not built and if a social system that can incorporate this new technology, and will see it as superior to existing technology, is not established (Stinchcombe, 1990). The example of the specialty chemical company turning a still-born invention into a significant product by changing the regulatory environment is one example. IBM's providing a stream of innovations to its clients, facilitated by the ongoing relationships with customers that their leasing contracts provided, is another example (Stinchcombe, 1990). This argument is consistent with the perspective that invention and innovation are a continuous process and it is difficult to distinguish one from the other. Furthermore, the profitability of the invention requires the cumulation of small improvements and the establishment of a social system, making revenue a compound indicator that combines technology, economic and social characteristics of the invention, the firm and its environment.

An important advantage of innovation surveys is to allow examining the drivers of innovation more broadly, in addition to R&D. Although R&D is a main source of innovation, technological progress can occur without formal R&D or from outside of R&D, with activities such as tooling, manufacturing, and marketing being important for successful production innovations (Mansfield, 1972; Mukhopadhyay, 1985). Many productive innovations have little to do with R&D activity, but originate in other ways such as the act of internal production through learning by doing and the cumulation of small suggestions from production workers, process

engineers and customers, as well as external acquisition (Stinchcombe, 1974). Nelson (1981)

states "learning by doing is an important part of the process by which new technology gets

created, modified, and broken in (p. 1047)." Moreover, Thomas (1994) argues that

manufacturing does not simply respond to the results of R&D but may also suggest product

innovation, so that experience in and understanding of manufacturing processes can open new

product possibilities. Therefore, the category "R&D spending", being an inadequate measure,

may ignore other important resources devoted to innovation (Solow, 1994, 2007). Along with

this perspective, there has been a rising interest in broadening innovation activities beyond R&D

among European studies (Arundel et al., 2008; Huang et al., 2011; Rammer et al., 2009),

demanding more research in US. This broadening perspective suggests the innovation potential

from outside of R&D, as well as R&D, and the need for a balanced approach to discussion of

innovation including non-R&D based innovation into the population of innovations. This work

suggests a need for broadening measures of the US innovation system.

3.4. Extending the population of innovations

In addition to highlighting the similarities and differences among innovation indicators, the

results in Tables 3.3 and 3.4 above present another important aspect of innovative activity. R&D

performers in manufacturing industries are less than 30% of total manufacturing firms (12.1% in

the NSF Survey of industrial R&D; 27.1% in DoIL). Since the overall rates of innovating firms

are about twice this high, this small percentage of R&D performers cannot be the only innovators

in their industry. Most firms do not conduct R&D and yet, evidently, many of them innovate.

Non-R&D performers have been less studied in the firm-level innovation studies (Cohen, 2010).

Also, innovation from non-R&D inputs, such as design activities, technical services, training,

and market exploration, has received much less attention (Smith, 2006). However, according to the 2011 BRDIS, out of all US firms, only 5% conduct R&D and out of all US *product* innovating firms (i.e. **firms** with at least one product innovation), about 72% are non-R&D innovators (i.e., innovating **firms** that do not conduct R&D), although R&D-active firms do have a higher probability of generating product innovation than non-R&D-active firms (58% vs. 7%). Moreover, out of **patents** issued, 94% is from R&D performers and 6% is from non-R&D performers (NSF, 2014). Moreover, out of patents issued, 94% is from R&D performers and 6% is from non-R&D performers. These results suggest that non-R&D innovation is an important complement to R&D-based innovation and needs to be explored further.

3.4.1. R&D vs. non-R&D innovation at the firm and project levels

To add new statistics of R&D and non-R&D innovation to current innovation statistics and motivate later discussion of what are possible problems and how we can create better indicators, this section tries to measure R&D and non-R&D innovation using private survey data which allow operationalization of different types of innovation using micro-level data. First, at the firm level, DoIL asked respondents about R&D activity for both innovators and non-innovators, whether or not they conduct R&D. Using these data, a firm that does R&D and has "new or significantly improved good or service (creating revenues)" (i.e. product innovation) is defined as an R&D product innovator, and a firm that does not conduct R&D and has a product innovation is defined as a non-R&D product innovator at the firm-level. The statistics by industry are shown in Table 3.5. The result shows that 45% of new to firm product innovators are non-R&D performing firms in US manufacturing industries (lower than the NSF statistic, i.e., 72% for all industries).

Table 3.5. Statistics of non-R&D product innovating firms in US manufacturing industries

Data source		DoIL					
		Innovator|RD		Innovator|NRD		NRD|Innovator	
		(Innovator % of R&D firms)		(Innovator % of non-R&D firms		(Non-R&D innovator %)	
		NTF	NTM	NTF	NTM	NTF	NTM
NAICS	N	(1)	(2)	(3)	(4)	(5)	(6)
311 Food	317	80.5	56.8	26.4	0.6	53.0	4.0
312 Beverage and tobacco product	62	83.5	70.4	27.1	0.0	45.5	0.0
313 Textile mills	41	74.6	56.5	27.3	0.0	32.6	0.0
314 Textile product mills	80	96.5	78.5	17.2	0.0	38.0	0.0
315-6 Apparel, leather and allied product	100	82.0	59.3	23.4	3.3	63.9	26.4
321 Wood product	79	85.3	62.0	12.0	0.0	50.6	0.0
322 Paper	129	84.3	68.3	15.1	1.8	39.7	8.9
323 Printing and related support activities	193	82.6	47.8	34.4	0.9	74.6	12.5
324 Petroleum and coal products	48	54.3	48.1	17.0	5.6	39.2	20.1
325 Chemical (except pharmaceutical and medicines)	327	81.0	48.3	15.9	0.0	13.9	0.0
3254 Pharmaceutical and medicine	133	71.9	37.1	36.2	9.3	17.8	9.6
326 Plastics and rubber products	350	83.0	54.0	30.5	1.8	45.1	7.5
327 Nonmetallic mineral product	339	69.3	49.6	21.0	1.1	60.1	10.9
331 Primary metal	333	75.3	45.6	28.1	1.7	60.5	14.7
332 Fabricated metal product	442	79.6	46.2	27.0	1.7	58.6	13.6
333 Machinery	400	80.6	58.8	22.5	0.0	31.2	0.0
334 Computer and electronic product (except semiconductor)	295	88.1	62.5	35.2	1.9	21.8	2.3
3344 Semiconductor and other electronic component	315	84.4	63.2	38.6	0.7	34.6	1.4
335 Electrical equipment, appliance, and component	326	85.7	59.3	33.3	5.4	33.3	10.8
336 Transportation equipment	362	85.7	67.7	25.6	1.2	31.0	2.4
337 Furniture and related product	271	96.4	70.5	28.4	2.5	58.9	14.8
339 Miscellaneous	399	90.3	63.0	32.5	1.4	37.8	3.9
All	5341	82.9	56.8	26.2	1.3	45.4	6.0

Note: Results are adjusted for sampling weights in columns (1) to (6).

However, the firm-level measures do not take into account that non-R&D innovation can be also created in R&D performing firms. For example, while the R&D department of an R&D-performing firm can generate innovations for the firm to introduce, the manufacturing or sales departments may also directly generate innovations that do not come from R&D. Thus, within such a firm, the innovations observed would be a mix of R&D and non-R&D innovations (although standard CIS-type indicators would define all of these as "innovations from R&D-performing firms"). Using a different approach, Arundel et al. (2008) show that 42.9% of in-house R&D performing firms introduce at least one product innovation without performing

R&D, based on the Innobarometer 2007 Survey data.[3] Although this is a more sophisticated statistic than other CIS-type indicators, in that it considers non-R&D innovation by R&D performing firms, it still represents a statistic of **innovators** who do R&D but produce at least one non-R&D innovation, not the **share** of non-R&D **innovations,** compared to R&D innovations, among R&D performers.

Therefore, to consider the population of innovations beyond the commonly used, population of innovators for innovation studies, and further develop our understanding of the innovation process, innovation is also measured at the project level, using triadically patented inventions from the US Inventor Survey as a proxy for innovation. While many (non-patented or US-only patented) firm inventions will not be included, the measure on triadic patents is capturing significant inventions because these patents are on novel technologies that were filed in three jurisdictions, suggesting they have high importance. Moreover, in contrast to other data, the Inventor Survey provides project-level data with inventors' information as employees and allows operationalizing R&D and non-R&D activity taking into account invention processes and employee's affiliation. However, since we only consider disclosed, highly important, inventions a proxy for innovation, the statistics on these data should represent the lower bound of innovations.

Using these project-level data, we create a measure of internally generated R&D v. non-R&D inventions. Defining R&D and non-R&D invention, first, requires understanding how people work in the firm to produce invention. An R&D employee's job is to create new knowledge by doing R&D. However, non-R&D employees such as sales, marketing, and

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[3] This statistic shows the percent of firms which do R&D but have any non-R&D innovation out of all firms with only R&D innovation, any non-R&D innovation or no innovation at all.

production employees sometimes join an R&D project with R&D employees through a cross-functional team. Thus, not only inventions by R&D employees but also inventions from cross-functional R&D projects should be defined as R&D inventions. However, if non-R&D employees who do not join an R&D project conceptualize the solution of a problem, it becomes a non-R&D invention.[4] Therefore, the type of employees and their creative process in producing the invention should be considered together in the work of defining R&D and non-R&D innovation at the project level. Based on this, we define R&D invention as: *invention from planned or organized problem-solving activities by the firm through R&D personnel, or R&D projects to produce new knowledge*, and non-R&D invention as: *invention from the production, sales, and other work activities of people whose job in their firm is not R&D and who were not involved in an R&D project related to the invention.*

To measure non-R&D invention, two questions about inventors' affiliation and their creative process in the Inventor Survey were used. The Inventor Survey provides information about inventors' affiliation (R&D units, R&D sub-unit attached to non-R&D such as manufacturing, manufacturing, sales/marketing, etc.) and their creative process (e.g. R&D

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[4] Some may argue that if R&D helped in the development of a non-R&D invention, then it should be categorized as an R&D invention. However, we argue that treating these as non-R&D inventions is consistent with the USPTO definition of "inventor". According to the USPTO Manual of Patent Examining Procedure [Chapters 2137 and 2138], the invention must be clearly conceived of in the inventor's mind (such that she could clearly describe it to another), but she does not have to carry out all the steps in the process to reducing the invention to practice (http://www.uspto.gov/web/offices/pac/mpep/mpep-2100.html). While "invention" requires "conception" and "reduction to practice", reduction to practice can be accomplished by the written description of the invention (Seymore, 2009), or by giving direction and guidance for other to carry out (USPTO guidelines). In our case, since we are dealing with patented inventions, with the (non-R&D) inventor certified by the patent office, this requirement has been fulfilled. Therefore, as long as the solution is clearly conceptualized in the course of the normal jobs of non-R&D personnel, although it is further developed in an R&D project later, following USPTO guidelines, this should be defined as non-R&D invention.

project, normal job, pure inspiration). As Table 3.6 presents, inventions from R&D units or R&D projects are defined as R&D inventions, and the rest as non-R&D invention. The cases of an R&D sub-unit attached to a unit with its primary focus on non-R&D, such as manufacturing, whose inventions are from their normal job (which is not inventing) or from pure inspiration/creativity were included as a non-R&D invention while those joining R&D projects were included as an R&D invention. R&D sub-units, especially those attached to non-R&D units, are generally more involved in technical services, which are non-R&D based on the Frascati manual (OECD, 2002) and NSF definition, than are independent R&D units, so that all inventions from employees in an R&D sub-units cannot be classified into R&D inventions.[5]

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[5] According to the Carnegie Mellon Survey data, when comparing R&D units located in production facilities and stand-alone R&D units, among business units with 10+ employees, the percentage of technical service (providing manufacturing support, troubleshooting, etc.) out of total "R&D" effort is substantially higher in subordinate R&D units than in stand-alone R&D units (23% v. 14% with total R&D budget as weight, $p < .01$). The Inventor Survey data also show that inventors from subordinate R&D units spend substantially more effort on technical service than those from independent R&D units (14% v. 7%, $p < .01$).

Table 3.6. Measures of R&D and non-R&D invention

	Location of the Inventor				
Creative process that led to the invention	Independent R&D unit or its sub-unit	R&D sub-unit attached to a non-R&D unit	Manufacturing	Software development	Other (e.g., sales)
Targeted achievement of a R&D project	R&D invention				
Unexpected by-product of a R&D project					
Expected by-product of a R&D project					
Related to your normal job (not inventing)		Non-R&D invention			
Pure inspiration/creativity					

Based on the measures at the project level, Table 3.7 shows that, out of all triadically patented inventions, about 12% of **inventions** are non-R&D inventions. As described earlier, BRDIS 2011 shows that out of all patented inventions, 6% of inventions are non-R&D inventions (NSF, 2014). However, since BRDIS defines all inventions from R&D performers as R&D invention neglecting non-R&D inventions in the R&D performing firms, it would underestimate the percentage of non-R&D inventions. Therefore, our statistics are broadly consistent with NSF data on patents (not just triadic patents). Of these non-R&D inventions, about a third comes from manufacturing units, about 20% comes from sales, service or other units, and the rest comes from R&D sub-units attached to manufacturing, etc. (i.e., technical service), or software development units. Moreover, these rates of non-R&D innovation vary across industries, implying industry-associated characteristics can drive relative differences in the rates of R&D and non-R&D innovation. In the Inventor Survey data, about 80% is product invention and there is no significant difference between R&D and non-R&D inventions in terms of which one is more associated with product invention ($p = .90$).

Table 3.7. Statistics of non-R&D inventions in US manufacturing industries

			Sources of NRD inventions			
		NRD|Invention	R&D subunit attached to non-R&D unit (e.g., technical service)	Manufacturing	Software development	Others (e.g., sales)
		(Non-R&D inv % of tradic patents)	(% of non-R&D inventions)			
NAICS	**N**	(1)	(2)	(3)	(4)	(5)
311-312 Food, beverage and tobacco product	5	0.0	0.0	0.0	0.0	0.0
313-316 Textile mills, textile product, apparel, and leather	10	21.4	0.0	100.0	0.0	0.0
321-323 Wood product, paper, and printing	21	20.8	80.0	20.0	0.0	0.0
325 Chemical (except pharmaceutical and medicines)	257	4.1	41.7	41.7	0.0	16.7
3254 Pharmaceutical and medicine	56	4.5	33.3	33.3	0.0	33.3
326 Plastics and rubber products	78	9.1	25.0	37.5	0.0	37.5
327 Nonmetallic mineral product	36	11.9	60.0	20.0	0.0	20.0
331 Primary metal	16	10.5	50.0	50.0	0.0	0.0
332 Fabricated metal product	74	19.5	31.3	50.0	0.0	18.8
333 Machinery	266	18.6	42.1	33.3	1.8	22.8
334 Computer and electronic product (except semiconductor)	441	12.9	28.4	28.4	16.4	26.9
3344 Semiconductor and other electronic component	177	11.7	53.9	23.1	15.4	7.7
335 Electrical equipment, appliance, and component	121	11.5	52.9	23.5	11.8	11.8
336 Transportation equipment	63	9.5	50.0	37.5	0.0	12.5
337-339 Furniture and related product, and miscellaneous	117	14.8	25.0	30.0	5.0	40.0
All	1738	12.1	38.6	32.1	7.6	21.7

Notes:

Due to slightly different industry classifications across different data sources, some numbers are displayed for merged industries from the classification in Table 3.5.

NAICS was assigned to each patent based on its product industry using the USPTO concordance between the U.S. Patent Classification System and NAICS.

Results are adjusted for sampling weights in columns (1) to (5).

As an additional analysis, these invention-level data are aggregated to the firm level to examine what percentage of total inventions in large R&D performing firms is non-R&D invention. Table 3.8 displays the 10 firms with the largest number of inventions in the Inventor Survey sample (each having a minimum of 15 patents in our sample). These top 10 most innovative firms all conduct R&D. The table shows that even R&D performing firms often produce non-R&D inventions, with an average of about 9% of the inventions in these large R&D performing firms being non-R&D inventions. The table also shows significant variation in the share of non-R&D inventions across these large, innovative firms, ranging from none to over 15%. These results show that non-R&D innovation is not just a small firm phenomenon, but that a significant share of the innovations of large R&D performing firms is non-R&D innovation. Note that since the statistics in Table 3.8 are drawn from patented inventions, the rates of non-R&D invention may be underestimated. If we include non-patented inventions, which may be higher in non-R&D invention than R&D invention, the rates would become larger.

Similarly, using the DoIL data, we can estimate, for new to market innovations (not limiting to patented inventions), among R&D performing firms, the share of those innovations that came from R&D versus non-R&D activity. The survey asked, for the firm's single largest innovation (in terms of revenue), "Did you introduce this innovation in your industry before any other company?" [i.e., was it new to market], and, "Did this innovation largely originate from R&D activity in your company?" [i.e., is this an R&D or non-R&D innovation?]. These questions then let us estimate the proportion of the (highest revenue) new to market innovations among R&D performing firms that did not originate in R&D. Of the R&D performing firms, 9% of their most important new to market innovations did not originate from R&D. Thus, using two different surveys, asking the question in slightly different ways, we find that, even in R&D

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performing firms, almost 10% of "important" (either triadically patented or new to market) innovations are non-R&D innovations.

Table 3.8. The share of non-R&D inventions by top 10 most innovative firms

Firm	% Non-R&D invention
A	16.1
B	15.2
C	13.8
D	13.5
E	13.0
F	4.3
G	3.1
H	0.0
I	0.0
J	0.0
All	8.7

Notes: All 10 firms are R&D performers.
All have at least 15 patents in our sample.
These 10 firms account for 357 patents (about 20% of the full sample).

3.4.2. Challenges of measuring R&D and non-R&D innovation

Although R&D and non-R&D innovation can be measured in several ways as discussed above, there still exist some challenges to conceptualize and measure R&D and non-R&D innovation. In many cases, non-R&D innovations are not disclosed because innovative ideas from outside of R&D can be easily suppressed by managers who consider it a dangerous source of inefficiency (Miner et al., 2001) or outside the bounds of work authority (Parker et al., 1997) or may not be visible because of political relations between management and non-management (Basu and Green, 1997; Halle, 1984; Thomas, 1994), although they are still active in generating new ideas. In particular, conflict between R&D and non-R&D personnel with low respect for each other can make non-R&D personnel not share their valuable knowledge with others (Halle, 1984; Thomas, 1994). Thomas (1994)'s analogy of doctor-patient relations provides useful insight about the

relation between R&D and non-R&D personnel. Sometimes patients understand the underlying

cause of their symptom based on their past suffering from a variety of ailments, but cannot

suggest too strongly their own diagnosis because doctors think they have authority of diagnosis

and that is their area (Thomas, 1994). Similarly, an inventor in an interview, working as a

salesman in the telecommunications equipment industry, found a huge commercial opportunity

through visiting customer facilities as part of his sales calls and began to think about a better way

to solve a problem that products from competitors were dealing with in a mediocre way.[6] When

he suggested his idea to R&D personnel in his company, they did not pay attention to his idea

and told him to concentrate on his own job, i.e. sales. Therefore, he had to develop his idea

through his own skunkworks, and finally invented a device for cleaning fiber optic connectors

that the company patented and developed into a major line of business. In contrast, another

inventor, who is an engineer working in an R&D lab in a consumer product company,

acknowledged the possibility of innovation from outside of R&D, but said, for example, that a

salesman could say a problem which keeps coming up from his customers and it would be nice if

it is solved, but deeper thinking is done by an R&D group.[7] He suspected that people outside

R&D may not come up with an idea as valuable as the R&D people and also the non-R&D

people do not think it through further, reflecting the attitude highlighted by Thomas (1994).

Moreover, there are cases where non-R&D employees may not want to tell them their

innovation. For example, an employee working at a clothing manufacturer in Chicago for more

than three decades developed her own way to sew a crotch in men's pants faster producing a

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[6] Inventor survey follow-up interview, conducted May 3rd, 2012.
[7] Inventor survey follow-up interview, conducted April 11th, 2012.

superior fit (Banks and Metzgar, 1989). Although the company made industrial engineers stand over her to watch how she did it, videotaped her work, and hired a time-and-motion study man, they could not figure it out, and she did not want to give management her knowhow, because of fear of losing control and status in her work, as well as distrust of management (Banks and Metzgar, 1989). The prevalence of this low respect for each other and strict work authority suggests that many non-R&D innovations may not be disclosed and measures of non-R&D innovation based on disclosed innovation would underestimate the real population. To the extent that this low respect and strong division of responsibility prevail, firms may generate fewer non-R&D innovations (Brown and Duguid, 1989; Thomas, 1994), and have access to only a fraction of those that are generated (Banks and Metzgar, 1989; Halle, 1984). This argument suggests that managerial practices can affect both the rate of non-R&D inventions generated and their availability for use by others besides the individual inventors, resulting in higher or lower rates of non-R&D innovation.

The other challenge is that depending on whether we focus on who owns the innovation or who creates the innovation, R&D and non-R&D innovation can be classified differently due to trade in technology and division of innovative labor (Arora and Gambardella, 2010). For example, if a firm acquires innovation which its customer created, it is the firm's innovation and called a user innovation (von Hippel, 2005). Focusing on who owns the innovation, if the owner firm conducts R&D, the innovation is classified as R&D innovation while if the owner firm does not conduct R&D, it is defined as non-R&D innovation. However, if focusing on who creates the innovation, the definition can change depending on whether the user does R&D or not. Furthermore, acknowledging that R&D performing firms can also create innovation from outside of R&D within the firm, the innovation can be created in either R&D or non-R&D in the

customer company and cannot be considered R&D innovation uniformly based on the fact that the customer company conducts R&D. There are also some fuzzy cases such as technical service which can be classified into either R&D or non-R&D. Although the Frascati manual and NSF classification include technical service into non-R&D, it may be hard for technical service employees who are also involved in R&D tasks to draw a clear line between technical service as non-R&D and their involvement in R&D. More interestingly, there can be also mismatch between perception by technical service employees and perception by outside observers. For example, in the earlier example of an interview about inventors working in a marketing division of a specialty chemical company and inventing a greener chemical, their main job is technical service for their customers. They claimed that their invention is non-R&D invention although outside observers may treat it as R&D invention. In another case, a manager from a metalworking firm with 30 years' experience worked with experienced production workers to develop a novel product based on solving a specific problem brought by a customer (how to form metal into a complicated shape).[8] While the initial part took over ten hours to make, movement down the learning curve resulted in cutting production time to about 15 minutes, and the result was a new product for this firm. The result was not patented but rather kept as a trade secret. As there is no R&D unit in this firm and as the employees involved are production workers and managers, should this be considered an R&D or non-R&D innovation? In these examples, even though inventors themselves state their job is not doing R&D and their invention is not from R&D, others might view this as R&D, despite those inventors' perception of their own inventions. It is not clear which criteria should be used: the international manual, inventors' own

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[8] Manager interview, conducted June 12th, 2014.

judgment, or each researcher's own operationalization. Therefore, conceptualizing R&D and non-R&D innovation is not simple line-drawing based on categorical R&D spending. Therefore, since it is hard to find exactly where we set the dividing line between these two, exploring different characteristics given the classification can help calibrate how to define this different type of innovation. More theoretical, qualitative and quantitative approaches are required to understand the fundamental differences between R&D and non-R&D innovation. In particular, there is a need for analyses of the conditions that generate different kinds of innovation (R&D and non-R&D) in order to find the extent to which these are distinct innovation processes (i.e., respond differently to environmental or organizational characteristics).

3.5. Conclusion

Innovation studies generally gloss over how innovation has been discussed in different contexts, simply employing a working definition, often based on the OECD manual. This chapter examines the meaning of innovation comparing commonly used indicators of innovation across different measures and across different data sources, and discusses how well or differently those measures reflect the meaning of innovation. When comparing indicators, especially within the same type, the mean value for the same industry tends to vary substantially across different data sources. However, we also observe high correlation among those indicators. Thus, it seems that the results are very sensitive to sampling strategies and to modes of data collection. This suggests that it may be difficult to match numbers from different data sources that measure the same concept; and that it may be better to focus on correlation across measures from different studies.

Comparing different indicators across industries, we see a split between patent-based indicators and R&D/CIS measures. For example, computer and electronic products (NAICS

334), and electrical equipment (NAICS 335) are highly innovative industries according to all indicators, while chemical (NAICS 325) and pharmaceutical (NAICS 3254) manufacturing are included in highly innovative industries only for the indicators of R&D and innovation, but not for the patent indicators. The characteristics of product technologies (e.g., discrete vs. complex) associated with a different number of patentable elements per innovation may especially affect patent-based indicators (Cohen et al., 2002). The factor analysis also shows that patents are distinguished from other indicators while R&D and innovation share a common factor. The existence of a shared latent variable driving R&D and innovation may be seen as a justification for using R&D as a proxy for innovation. However, conflating innovation and R&D ignores the leap between R&D as an input and innovation as an output, and furthermore, excludes innovation from other activities outside R&D, what we term non-R&D based innovation, which should be included in the population of innovations and may be systematically different from R&D based innovation. Therefore, R&D cannot be equated to innovation, although it is highly correlated with innovation, but rather may be better understood as one input for creating new ideas or facilitating adoption. Moreover, the results of these comparisons indicate that the concern about how to define innovation and its significance raise the need for extending the current view. Extending the population of innovations, this study also suggests a possible operationalization of R&D and non-R&D innovation and present statistics of R&D and non-R&D innovations and innovators using existing data. Although it may be difficult to draw a clear dividing line between R&D and non-R&D, initial results based on a variety of datasets show that non-R&D innovation is prevalent and that the rates of R&D and non-R&D innovation vary by industry. For example, the NSF data shows that 72% of product innovating **firms** in all US industries do no R&D; the DoIL data shows that 45% of innovating **firms** with at least one new-

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to-firm product innovation and 6% of innovating **firms** with at least one new-to market product innovation in US manufacturing industries are non-R&D innovators. We also find, using the Inventor Survey data, 12% of triadically patented inventions come from non-R&D. Furthermore, from the DoIL data, even among R&D performing manufacturing firms, almost 10% of new to market innovations are non-R&D.

The comparison of existing innovation indicators guides us to the understudied area of non-R&D based innovation. The study of non-R&D innovation contributes to better tapping innovation management and policy understandings of the organizations of innovation to create a more balanced view of the innovation system and capturing the neglected innovation economy. Considering non-R&D innovation is especially important for policy. For example, current policy such as R&D tax credits (generated from the R&D-centered view in innovation policy) consequently subsidizes one kind of innovation, R&D innovation, although this may not be what this policy actually intended. Moreover, while innovation from R&D has been assumed to have more spillover effects than that from other activities (and hence worthy of subsidy) thereby considered more important in policy, it is not always better. What we want may be the limited spillover effects within country, not across countries or all over the world, because we still want to keep our competitive advantage. In this sense, broader spillover effects by R&D-driven technologies cannot always be considered better than relatively narrower spillover effects by non-R&D-driven technologies. Rather, non-R&D-driven technologies may spill over across units within a firm or across agents within a region, bringing the moderate spillover effects but still keeping the region competitive. Therefore, non-R&D innovation has different characteristics and values worth considering.

These results in this chapter suggest there may be fruitful research opportunities exploring the distinct characteristics of diverse forms of innovation to better conceptualize innovation and its drivers. This broadened research agenda may also provide opportunities to develop an integrated perspective on the stages and prevalence of innovation in different functions in an organization and suggest that innovation policy is not only about R&D. This effort can contribute to developing strategy for producing different types of innovations, creating better science and innovation policy indicators, and developing innovation policy that accounts.

CHAPTER 4

INVENTING WHILE YOU WORK: KNOWLEDGE GENERALITY, VISIBILITY AND NON-R&D INNOVATION

4.1. Introduction

Innovation is widely recognized as a key to economic growth (Romer, 1990; Rosenberg, 1982). However, most research on the innovation process has focused on the results of R&D projects (Cohen, 2010). The positive relation between R&D intensity as an input and innovative performance as an output has become the canonical image for research on innovation (Cockburn and Griliches, 1987; Wakelin, 2001). While R&D is an important input to innovation, there is growing evidence that a significant share of innovation is not born from R&D (Arundel et al., 2008; Heidenreich, 2009; Hervas-Oliver et al., 2012; Mansfield, 1972; Rosenberg, 1982; Solow, 2007). Recent work on European firms finds that about half of innovating firms do no formal in-house R&D (Arundel et al., 2008; Huang et al., 2011). There is also some evidence that non-R&D performers relatively more focus on process innovation compared to R&D performers (Arundel et al., 2008). Moreover, non-R&D performers (or innovators), compared to their R&D counterparts, rely relatively more on innovation management tools such as human resource management and team work or marketing and organizational innovations to compensate for the lack of R&D capabilities (Heidenreich, 2009; Rammer et al., 2009). These studies suggest that non-R&D activity is an important input for innovation and that non-R&D innovators have different characteristics from R&D innovators. The broader view on innovation capacity is based on the prevalence of learning and innovation from work activity (outside of R&D as well as R&D) within an organization (Asheim and Coenen, 2006; Nelson, 1981). Furthermore, it calls

for examining the importance of the actual knowledge bases of various industries shaping learning processes of firms, in particular, different learning processes between intentional learning (e.g., R&D) and learning as a by-product of routine economic activities (e.g., learning by doing, using, or interacting in the course of normal production, marketing and sales) in a firm (Asheim and Coenen, 2006; Jensen et al., 2007; Lundvall and Johnson, 1994).

Building on this path and extending prior research, this study has the following goals. First, using US invention-level data, we characterize non-R&D innovation compared to R&D innovation. This process will show that firms, especially R&D performing firms, have both R&D and non-R&D innovation and that non-R&D innovation, while having distinct characteristics, is not simply incremental or process innovation, but also may be as valuable as R&D innovation. Prior work in the history of technology shows that a significant share of product development and improved productivity comes from the accumulation of such innovations, often generated by craftsmen and mechanics' solving problems in their daily operations and marketing and sales employees' pursuing of new product ideas outside of a formal R&D project, and adds substantial value to the firm beyond R&D innovation (Lundvall and Johnson, 1994; Rosenberg, 1982).

Second, we focus on the originator of innovation, with a direct link between invention and the origin activity in the firm. While some prior research sees innovators in terms of ownership of innovation, for example, with the classification of technology adopter or innovator that is a contract R&D performer as well as in-house innovator (Arundel et al., 2008; Huang et al., 2011), this study sees innovators in terms of origination of innovation. In our sample, all innovations are internally generated in the inventing firm, before being traded in the market. Therefore, our data include births of innovation and allow us to analyze learning and innovation within an organization (distinct from markets for technology).

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Third, nature of knowledge shapes the learning and innovation processes of firms (Asheim and Coenen, 2006; Asheim and Hansen, 2009; Cohen and Levinthal, 1989; Jensen et al., 2007). Based on existing learning and innovation literatures, we study how different nature of knowledge enhances the role of R&D and non-R&D employees for innovation in firms. In particular, we analyze the second-order effects of learning by R&D and non-R&D on innovation contingent on dominant knowledge characteristics in industries, that is, in which knowledge environment the effect of non-R&D on innovation gets larger relative to R&D or vice versa, given the relative size of R&D and non-R&D (i.e., given R&D intensity). We test these relative second-order effects using the unique structure of our invention-level data. Prior work, first, shows the first-order effects of R&D and non-R&D, finding that the more investment in R&D and/or non-R&D activity (such as training, marketing and design), the more likely for the firm to generate an innovation or different types of innovation (product or process) (e.g., Arundel et al., 2008). Extending, but different from, these prior studies, we characterize knowledge environments where firms operate in terms of generality (with high mobility or transferability) and visibility of knowledge, and analyze their effects on differences in the effect size of R&D and non-R&D learning on innovation.

Fourth, this study focuses on estimating the base rate of relative effectiveness of R&D and non-R&D learning on innovation within a firm in terms of nature of knowledge. Estimating the change in the base rate in different knowledge environments will be the first step to study non-R&D innovation in the US, and further help stress and develop future studies of how we can change the rate, introducing more effective firm strategy, management tools or organizational structures (Lundvall and Johnson, 1994; Rammer et al., 2009).

Finally, we contribute to international statistics on non-R&D innovation. Non-R&D innovation has been less studied in the US. Using novel data on the US, this study will add new evidence of non-R&D innovation with comparative analysis to R&D innovation and by including relatively high-tech environment such as the US, expanding the international study of innovation.

The structure of this chapter is as follows. We, first, will describe learning rooted in non-R&D activity, distinct from learning in R&D, and discuss how this can explain an underexplored category of innovation, i.e., non-R&D innovation. Second, we discuss how different knowledge environments affect different innovation productivity given R&D and non-R&D through their distinct learning. Third, we test hypotheses built from the theory using an integrated dataset built from several data sources. Lastly, we conclude with results, implications, and future studies.

4.2. An extended view: distributed locus of innovation within an organization

Organizations can learn and innovate through a variety of processes (Malerba, 1992). Figure 4.1 characterizes innovation by locus of internal activity and type of innovation. The framework in Figure 4.1 does not draw a pure typology by origin and type of innovation, because, for example, sometimes innovation can be related to both product and process and also because there can be ambiguity about where the solution is conceptualized. However, this ontological framework with concepts and contrasts in innovation types is still useful to understand how innovations are created through different mechanisms (Winter, 2003).

Organizations learn from direct experience. Learning by doing increases efficiency because workers improve their competencies in repeated procedures, which increases the frequency of successful output (Levitt and March, 1988). Libertyship building, aircraft

production and nuclear plant operation are well-known examples in the learning by doing literature (Benkard, 2000; Joskow and Rozanski, 1979; Thompson, 2012). Although simple adaptation or improved competencies over time in the production process enhance productivity, workers sometimes develop better ways to solve errors in the procedures beyond autonomous learning by doing. For example, in their study of learning in pizza franchises, Argote and her colleagues gave the examples of the improvement of the pepperoni placement procedure for pan pizzas, going from distributing the pepperoni equally over the pie to placing it in spokes around the pie, to avoid pepperoni mounded in the center after baking (Darr et al., 1995); a 'cheese spreader' tool developed to distribute cheese evenly over the entire pizza; and a 'proofing' method of checking pizza dough by pinching it to see if the dough springs back into place (Argote and Darr, 2000). These examples of process innovation through learning by doing are positioned around area (A).

While the organizational learning literature discusses learning by cumulative experience, there is another stream of literature that argues that learning in the production process may be through R&D rather than direct production experience (Area (B) in Figure 4.1). Hatch and Mowery (1998) show that learning by doing in the semiconductor industry is the result of allocating engineering resources to learning in the context of new process introduction and analyzing production data to solve problems rather than a by-product of production experience. Similarly, Sinclair et al. (2000) show in the case of a specialty chemical manufacturer that learning by production experience, measured by cumulative past output, does not directly affect cost reduction, but rather increases incentives to do process R&D or influences the choice of R&D projects, which generate cost reductions. They argue that R&D personnel or chemical engineers perform the actual experiments and modify production processes, and, therefore, they

conclude, even learning by doing is largely the result of R&D activity. Thus, organizational

learning and innovation literatures have suggested that learning by cumulative experience is

mostly related to process improvement, and even that might be by R&D, and product innovation

is mainly driven by formally organized innovative effort, or R&D, as represented by area (C)

(Aoki, 1991; Cohen, 2010; Kemp and Pearson, 2007).

Type of innovation

	Process	Product
R&D	(B)	(C)
Non-R&D	(A)	(D)

Origin of innovation

Figure 4.1. Framework of origin and type of innovation

However, these perspectives neglect the possibility of informal deliberate learning and

innovation (including product innovation) in non-R&D activity. For example, for process

innovations, Halle (1984) finds in his study of chemical engineers and production workers in a

chemical plant that production workers routinely experiment and innovate in the production

process. However, production workers have interests in hiding all shortcuts and secrets from

management, in order for the workers to make their work easier and control their work pace.

Hence, their innovations in productivity may not appear in the accounts, such as the official

record of how long a batch took or how many times ingredients were added to the batch (Halle,

1984).[9] Production workers can make improvements in production and modify their equipment, which can eventually create significant changes from the original design (Kusterer, 1978). Thomas (1994) also finds in an aluminum company that operators in a production factory sometimes keep a "little black book" documenting their work history, saving original blueprints and recording the tricks they had used to run a difficult operation. These examples suggest that process innovation may be the result of deliberate study by non-R&D employees, beyond simple improvements in skill gained from experience. Moreover, Thomas points out that conventional thinking in organization theory, which sees manufacturing or other functions outside R&D as relatively powerless in innovation, leads firms to underuse valuable knowledge in manufacturing that could provide competitive advantage to the R&D unit, and does not recognize the potential for manufacturing to also generate product innovation, not just process improvements (Area (D) in Figure 4.1). Thus, not only R&D, but also non-R&D activity such as production contributes substantially to firm innovation. Whether those improvements show up in the formalized accounting of innovations or in productivity data is in part a political or organizational matter related to relations between production and management and the organizational structure helping those improvements get expressed (Banks and Metzgar, 1989; Basu and Green, 1997; Kenney and Tanaka, 2003; Miner et al., 2001; Parker et al., 1997; Vallas, 2003).

Thus, non-R&D innovation needs to be examined more comprehensively, including coverage in a high-tech environment such as the US and in large firms (Asheim and Coenen,

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[9] Sinclair, et al. (2000) also note that there can be a disconnect between actual productivity and the cost accounting records of productivity. For example, sometimes batches sit in a vat and get charged costs for the vat, but only because there is a back-up in the next step, not because workers are using the vat, which would inflate the costs and make productivity appear lower than it actually is.

2006), as well as examining within-firm differences in innovation from R&D and non-R&D activity. According to the 2011 Business R&D and Innovation Survey (BRDIS) by NSF, out of all US firms, only 5% conduct R&D and out of all US *product* innovating firms, about 72% are non-R&D innovators, although R&D-active firms do have a higher probability of generating product innovation than non-R&D-active firms (58% vs. 7%) (NSF, 2014). Moreover, out of patents issued, 94% is from R&D performers and 6% is from non-R&D performers. Note that these statistics are all still limited to the firm level, neglecting non-R&D innovation in R&D-active firms. To develop this expanded understanding of innovation, we examine the rates of R&D and non-R&D innovation and how these vary by knowledge environments. The next section discusses how nature of knowledge shapes innovation processes differently for R&D and non-R&D activity in an organization.

4.3. Nature of knowledge, learning and innovation in R&D vs. non-R&D

To explore innovations from non-R&D compared to R&D in an organization, we should expand our understandings of learning and innovation. As we discussed in the previous section, learning and innovation are often thought of as something that happens outside the ordinary workplace. However, Jensen et al. (2007), in their extended view on learning, describe that firms have two different modes of learning: Science, Technology and Innovation (STI) mode relying on science and technical knowledge and Doing, Using and Interacting (DUI) mode depending on informal processes of learning, experience-based know-how and user needs. Moreover, Brown and Duguid (1991), based on the practiced-based view of learning, contend that learning is not separate from working and spans between working and innovating. Thus, the dominant view of learning by R&D, which values abstract knowledge over actual practice, does not recognize

learning in working and misses many potential innovations generated from learning in working (Brown and Duguid, 1991; Jensen et al., 2007). Subsequent improvements in technology, which account for the bulk of technological changes, and the pace of improvement, result from feedback from earlier experience in working (Rosenberg, 1976). As we develop below, this feedback will be more effective if the production process and products are more visible. The ongoing activity of production, sales, marketing and other work besides R&D will also inspire creativity in the non-R&D employees (Brown and Duguid, 1991; Rosenberg, 1982; Smith, 1776; Solow, 1994). Therefore, "learning by doing [or by using or in working] is an important part of the process by which new technology gets *created*, modified, and broken in (p. 1047)" (Nelson, 1981). Although generating inventions is not non-R&D personnel's primary role, while doing their normal job, some of them develop new ideas. Such extra-role behavior is common in organizations and is seen as a key to organizational effectiveness (Organ, 1988; Walsh and Tseng, 1998). Extending the prior work, we argue below that it is differences in the knowledge environments that drive the relative effectiveness of R&D and non-R&D activity for generating innovations.

Thus, firms have two different modes of learning and nature of knowledge will affect different intensities of the two modes of learning in firms, enhancing the role played by one more than the other (Jensen et al., 2007; McIver et al., 2013). The effect size of R&D and non-R&D learning on innovation is not constant, but varies by nature of knowledge. In the next sections, we examine particular knowledge environments and their impact on differences in the effects of R&D and non-R&D learning on innovation (i.e. second-order effects).

4.3.1. General knowledge environment and R&D vs. non-R&D innovation

Asheim and Coenen (2006) theorize "the actual knowledge base of various industries strongly shapes the innovation processes of firms". Based on this theory, the nature of knowledge of various industries should further affect the innovation processes of different activities in firms. Prior research characterizes knowledge bases slightly differently, though sharing similar underlying characteristics. Asheim and Coenen (2006) and Asheim and Hansen (2009) distinguish "analytical" knowledge, which is science-based, formal and codified, from "synthetic" knowledge, which is relatively more engineering-based and path-dependent. Jensen et al. (2007) characterize forms of knowledge into explicit, global knowledge, which enhances the role of STI mode learning, and implicit, local knowledge, which enhances the role of DUI mode learning. Pavitt (1984) and Winter (1984) distinguish between entrepreneurial regime, favorable to science-based innovative activity, and routinized regime, favorable to innovative activity by cumulative learning. These characterizations by prior work are commonly related to the generality of knowledge. Context-specific knowledge is sticky and hence difficult to apply in different contexts whereas general and abstract knowledge, articulated in universal terms and based on codified scientific and technical information, is less context dependent, more readily applicable in diverse contexts, and potentially moves the locus of problem-solving (Arora and Gambardella, 1994; Asheim and Isaksen, 2002; Kenney and Dossani, 2005; Pavitt, 1984; von Hippel, 1994). Therefore, the environment where general knowledge is more important matches work practices and enhances the role by R&D employees which apply principles they learn in their higher science and engineering education and test hypotheses, with the ability to use sophisticated instruments and devices (Arora and Gambardella, 1994; Jensen et al., 2007; Stinchcombe, 1990). On the other hand, in an environment where sticky knowledge is more

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important, innovative activity by skilled, non-R&D employees becomes more effective, and computer simulation and laboratory analyses are less likely to anticipate problems (Asheim and Coenen, 2006; Lüthje et al., 2005; Malerba, 1992). Therefore, along a continuum of importance from general to sticky knowledge in an environment, the higher importance of general knowledge in an environment will enhance the role by R&D more than that by non-R&D, and the higher importance of sticky knowledge in an environment helps non-R&D be relatively more effective in learning and innovation compared to R&D. In other words, the ratio of the non-R&D learning coefficient to the R&D learning coefficient will increase, i.e. that non-R&D activity will be relatively more efficient, compared to R&D activity, at producing innovations in a sticky environment than in a general knowledge environment.

Although prior studies theorize the importance of nature of knowledge to learning and innovation, their empirical analyses are mostly limited to testing a part of this theory, for example, showing the effect of knowledge characteristics (e.g., ease of learning by targetedness of outside knowledge to the firm) on investment in R&D to increase learning (Cohen and Levinthal, 1989, 1990), or the importance of different learning modes to innovation (Jensen et al., 2007). Extending from this prior research and taking nature of knowledge, different modes of learning (by R&D and non-R&D) and innovation simultaneously into account, we analyze how knowledge environments create differences in the effects of two different learning modes on innovation in a firm. The importance of general knowledge in an environment may increase demand of R&D, thereby eliciting more investment in R&D given sales revenue (cf. Cohen and Levinthal, 1990). However, it will further affect the relative effectiveness of learning by R&D and non-R&D for innovation, controlling for R&D intensity of the firm. Understanding this underlying mechanism, we will show that given the relative size of R&D and non-R&D activity

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in the firm (R&D intensity), the higher importance of general knowledge in an environment increases the effect of learning by R&D on innovation more than that of learning by non-R&D on innovation (i.e. relative differences in second-order effects of learning). Put differently, our argument is that the R&D activity in the firm will benefit more (in terms of producing innovations) from this knowledge than will the non-R&D activity. This leads to the following hypothesis:

H1: The higher importance of general knowledge in an environment, the greater probability of a firm's generating R&D innovation relative to non-R&D innovation, net of firm R&D intensity.

4.3.2. Visible knowledge environment and R&D vs. non-R&D innovation

The effectiveness of learning also changes in the face of more opportunities to apply knowledge earned through work. Organizations that assume learning as an information-transmission process (i.e. non-R&D personnel are told what they need to know) tend to produce and adopt opaque technologies (Brown and Duguid, 1989). This makes non-R&D learning more difficult because the technology or problem is not visible to them, and this reinforces the assumption that non-R&D personnel cannot learn on their own, making technology more and more opaque and creating a negative feedback loop (Brown and Duguid, 1989). By visibility, we mean the extent to which those engaged in the production of the product/service can see problems and can see how their own actions affect the outcomes (i.e., there are tighter links between actions and outcomes). Furthermore, more visible problems recurring frequently will provide more opportunities for creative thinking and utilizing learning by doing or in working, and get solved faster, thereby contributing to the introduction of more innovations given

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investment in learning activity in an organization (Kenney and Tanaka, 2003; Winter, 2003). A production technology with low visibility of problems and high uncertainty in the production process makes the links between activities and their consequences harder to discern, making innovation opportunities less likely to be recognized (Brown and Duguid, 1989).

This visibility of problems is affected by organizational structure (Lundvall and Johnson, 1994; Van de Ven et al., 1976). Organizational structures that make problems more visible are associated with more opportunities for enhancing and utilizing learning by doing, using and interacting (Jensen et al., 2007). For example, the Toyota Production System, which specifies activity for each worker and tightly-linked sequential processes, makes problems more visible and provides more opportunities for learning to be utilized in the organization (Spear and Bowen, 1999).

However, not only organizational structure, but technology or knowledge itself can also have more visible characteristics in certain activities or industries. In Argote and Darr (2000)'s example of the 'cheese spreader', the problem of unevenly distributed cheese is obvious to all those who work in the store, while developing a 'proofing' method for pizza dough requires more time and experimentation because of the weak links and low visibility between the dough making process, the nature of the dough and the outcome (i.e. good or bad pizza). In the case of many mechanical industries, the product components and their interactions may be relatively more visible, when compared to, for example, chemicals, materials or electronics products (Seymore, 2009). For example, in the process of designing the new V-Rod motorcycle, Harley-Davidson production engineers could readily spot production problems inherent in early designs simply by looking at a steel and clay prototype (Sichterman, 2001). Owan and Kim (2013) show that opportunities for problem solving are greater in some product segments than others because

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of the visibility of problems in those products. For example, most semiconductor products are "black box", so that problems are not visible when they work poorly. However, the elements of a memory chip are individually addressable, so the specific nature of problems is more easily spotted and solved (Owan and Kim, 2013). Owan and Kim (2013) show higher rates of learning by doing in memory chip production than in other segments, consistent with this visibility argument.

Therefore, greater ease of seeing problems will be associated with more opportunities for utilizing learning by non-R&D, increasing the effect of non-R&D learning on innovation. The high visibility of problems will also affect learning by R&D. However, the effect of visibility on learning and innovation of non-R&D will be relatively larger than that on those of R&D because R&D, whose main job is inventing, will be relatively less sensitive to visibility of problems in production (and also more removed from direct interaction with the production process). Therefore, the relative difference in effects of R&D and non-R&D learning on innovation will be smaller in high visibility. Accordingly, we have the following hypothesis:

H2: The greater visibility of knowledge in an environment, the lower probability of a firm's generating R&D innovation relative to non-R&D innovation, net of firm R&D intensity.

4.4. Data and methods

4.4.1. Data

The focal data in this study are from the US Inventor Survey. The Inventor Survey is a survey of US inventors on triadic patents (patents filed in Japan and the EPO and granted by the USPTO) in the application period 2000 to 2003, and collects information on the projects that generated the

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patent, which allows us to code whether this was an R&D or a non-R&D invention (Walsh and

Nagaoka, 2009). The survey sampled triadic patents stratified by NBER technology classes.[10]

The number of patents belonging to each unique inventor was recorded to use as a weight for

later survey data estimation. The survey received 1919 responses with a response rate of 24.2%

(31.9% adjusted for undelivered, deceased, etc.).[11] After limiting data to patents assigned to

firms (i.e., excluding universities and hospitals, government labs and individual inventions), the

sample used in this study includes 1738 triadic patents. We combined the Inventor Survey data

with Carnegie Mellon Survey (CMS), NSF, and US Census data. The CMS is a 1994 survey of

R&D managers in R&D units located in the US conducting R&D in manufacturing industries as

part of a manufacturing firm, and includes information about knowledge sources, which allows

us to create measures of the knowledge environment (Cohen and Walsh, 2000). The NSF R&D

in Industry data in 1999 (NSF, 2002) and US Census provide industry R&D and sales data prior

to the Inventor Survey. To combine those data, we create industry concordances among the three

datasets building from the US Census SIC-NAICS concordance between the CMS and NSF/US

Census and the USPTO US patent class-product industry NAICS concordance between the

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[10] To limit respondent burden, we randomly selected one patent out of multiple patents belonging to the same inventor

[11] To test for non-response bias, we used data from the patent documents to compare respondents to non-respondents. We find little evidence of non-response biases that were either statistically or substantively significant. In particular, measures of collaboration (solo inventions: 27% for respondents, 26% for non-respondents; average number of inventors: 2.71 for respondents, 2.80 for non-respondents), links to universities (citations to non-patent literature: 2.4 for respondents, 2.7 for non-respondents) and measures of patent value (forward citations, 2.2 for respondents, 2.4 for non-respondents) are all similar (none are significantly different, $p<.05$, N=7933). The only significant differences are that inventors for which we only had a company address (instead of home address) are less likely to respond (4% of respondents had a company address v. 6% for non-respondents, $p<.001$) and those with more patents are more likely to respond (mean of 1.18 patents for respondents, 1.13 for non-respondents, $p<.001$), although the absolute differences are quite small. Thus, despite the modest response rate, we have some confidence that our sample is representative of the underlying population of US-based inventors on triadic patents.

Inventor Survey and NSF/US Census.[12] Therefore, environment, or industry, variables for the invention represent the characteristics of the industry that is related to the patented technologies (which may be different from the NAICS classification of the firm). These "projects in firms" data allow us to control for firm-level and technology-level industry characteristics in the same model. All knowledge environment variables are at the 3-digit 2007 NAICS covering US manufacturing industries. The following sections describe project-level definitions of R&D and non-R&D innovation and explain the empirical model.

4.4.2. Measures of R&D vs. non-R&D invention

Innovation in this study is measured at the project level, using triadically patented inventions as a proxy for innovation. Although using patents as a measure of innovation is problematic, in this case, these are significant inventions because these patents are on novel technologies that were filed in three jurisdictions, suggesting they have high importance (Grupp and Schmoch, 1999). Thus, while many (non-patented or U.S.-only patented) firm inventions will not be included, we have some confidence that we are capturing significant inventions. Using these data, we can create a measure of internally generated R&D v. non-R&D inventions.

Defining R&D and non-R&D invention requires understanding how people work in the firm to produce invention. An R&D employee's job is to create new knowledge by doing R&D. However, non-R&D employees such as sales, marketing and production employees sometimes join an R&D project with R&D employees through a cross-functional team. Thus, not only

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[12] Some patent classes have multiple relevant product industries. In this case, we randomly sample one industry.

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inventions by R&D employees but also inventions from cross-functional R&D projects are defined as R&D inventions. However, if non-R&D employees who do not join an R&D project conceptualize the solution of a problem, it becomes a non-R&D invention. Therefore, the type of employees and their creative process in producing the invention should be considered together when defining R&D and non-R&D invention at the project level. To define non-R&D invention, we employ two questions from the Inventor Survey: one about the creative process that led to their invention and one about the type of unit to which they belonged at the time of the invention. The question about the creative process is as follows:

Which of the following scenarios best describes the creative process that led to your invention?

a. The **targeted achievement** of a research or development project

b. An **unexpected by-product** of a research or development project

c. An **expected by-product** of a research or development project

d. Directly **related to your normal job** (which is not inventing), and was then further developed in a (research or development) project

e. From **pure inspiration/creativity** or from your normal job (which is not inventing), and was not further developed in a (research or development) project

The inventors' affiliation is categorized by the following units:

1. An independent R&D unit or its sub-unit

2. R&D sub-unit attached to a unit with its primary focus on non-R&D such as manufacturing

3. Manufacturing

4. Software development

5. Other (e.g. Sales/marketing)

The inventions from (a, b, c) OR (1) are defined as R&D invention. Therefore, if people in non-R&D units produce an invention as a result of joining an R&D project, it is classified into R&D invention (OECD, 2002). In contrast, inventions from (d, e) AND (2, 3, 4, 5) are defined as non-R&D invention (see Seymore, 2009, for a discussion of the requirements for "inventor").[13] The counts of inventions in each cell are displayed in Table 4.1.

Table 4.1. Measures of R&D and non-R&D invention

Creative process that led to the invention	Location of the Inventor						Total
	Independent R&D unit or its sub-unit	R&D subunit attached to a non-R&D unit	Manufacturing	Software development	Other (e.g., sales)	.	
Targeted achievement of a R&D project	626	147	63	19	33	7	895
Unexpected by-product of a R&D project	132	35	12	10	10	2	201
Expected by-product of a R&D project	123	49	6	10	3	1	192
Related to your normal job (not inventing)	97	43	31	7	21	0	199
Pure inspiration/creativity	129	39	37	10	31	0	246
.	5	0	0	0	0	0	5
Total	1112	313	149	56	98	10	1738

Colored cells defined as non-R&D invention.

[13] Some may argue that if R&D helped in the development of a non-R&D invention, then it should be categorized as an R&D invention. However, we argue that it is consistent with the USPTO definition of "inventor" to treat these as non-R&D inventions. According to the USPTO Manual of Patent Examining Procedure [Chapters 2137 and 2138], the invention must be clearly conceived of in the inventor's mind (such that she could clearly describe it to another), but she does not have to carry out all the steps in the process of reducing the invention to practice (http://www.uspto.gov/web/offices/pac/mpep/mpep-2100.html). While "invention" requires "conception" and "reduction to practice", reduction to practice can be accomplished by the written description of the invention (Seymore, 2009), or by giving direction and guidance for others to carry out (USPTO guidelines). In our case, since we are dealing with patented inventions, with the (non-R&D) inventor certified by the patent office, this requirement has been fulfilled. Therefore, as long as the solution is clearly conceptualized in the course of the normal jobs of non-R&D personnel, although it is further developed in an R&D project later, following USPTO guidelines, this should be defined as non-R&D invention.

In the cases of an R&D sub-unit attached to a unit with its primary focus on non-R&D (such as manufacturing), if those inventions are from their normal job (which is not inventing) or from pure inspiration/creativity, they were included as a non-R&D invention. Subordinate R&D units (item 2 in the unit question) are likely heavily involved in technical services, compared to independent R&D units (item 1 in the unit question), so we should not assume that all inventions from employees in such sub-units should be classified *a priori* into R&D inventions (if the answer to the question about the invention process suggests these were not part of an R&D project) consistent with the Frascati manual and NSF's classification, which exclude "production and related technical activities" from R&D (OECD, 2002). According to the CMS data, when comparing R&D sub-units located in production facilities and stand-alone R&D units, among business units with 10+ employees, the percentage of technical service (providing manufacturing support, troubleshooting, etc.) out of total "R&D" effort is substantially higher in subordinate R&D units than in stand-alone R&D units (23% v. 14%, $p < .01$). The Inventor Survey data also show that, on average, inventors from subordinate R&D units spend substantially more effort on technical service than those from independent R&D units (14% v. 7%, $p < .01$). Therefore, reflecting the different characteristics between subordinate R&D units and stand-alone R&D units, if, based on the answer to the invention process question, employees from subordinate R&D units are not involved in a planned, official R&D projects leading to the invention, their inventions can be defined as non-R&D inventions, e.g., from their technical service or pure inspiration.

To validate our measure and learn more about actual cases of non-R&D invention, we interviewed several inventors, and examined written comments by respondents in the Inventor Survey and patent documents. Despite general perceptions, not all non-R&D product innovations

are meager, trite innovation. For example, one inventor in our interview was working as a salesman in the telecommunications equipment industry.[14] He found a huge commercial opportunity through his business relationships and began to think about a better way to solve a problem that products from competitors were dealing with in a mediocre way. When he suggested his idea to R&D personnel in his company, they did not pay attention to his idea and told him to concentrate on his own job, i.e. sales. However, the commercial opportunity he saw pushed him to keep developing his idea through a skunkworks, invoking the help of his business relationships with distributors and customers (so called "business friendships" in his words), visiting a local research university library for leads, and testing different materials. Based on an inspiration gleaned while driving home from a meeting one day, he developed a prototype in his basement and invented a device for cleaning fiber optic connectors that the company patented and developed into a major line of business. In another case, a technical service representative in the marketing division of a specialty chemical company received a complaint from his customers about a widely-used but potentially toxic chemical, and saw an opportunity for a greener solution.[15] Armed with a decade of customer service experience and an undergraduate degree in chemistry, he came up with a new solution, a greener coating for ships, that was patented and which became a core business of the firm. In these cases, the invention grew not from formal R&D projects designed to solve the problem, but from sales employees seeing a customer problem and recognizing a viable novel solution based on their existing knowledge base. Note

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[14] Inventor survey follow-up interview, conducted May 3rd, 2012. As part of the inventor survey, we interviewed several inventors to gain more details about the invention process that led to their triadically patented invention. We also interviewed additional inventors and managers about other non-R&D inventions.

[15] Inventor survey follow-up interview, conducted August 9th, 2012.

that technical service is not R&D based on the Frascati manual and NSF classification (OECD, 2002) and that neither interviewee was informed that he was classified as a non-R&D inventor in this study. The interviewees self-claimed that they were not in R&D projects and their inventions are not from R&D. There may be confusion of these examples with user innovation (von Hippel, 2005). We would like to clarify this is not a user innovation because problems were not solved by their customers, although problem choices were driven by customers in the course of those inventors' normal jobs. Non-R&D inventions can also come from the daily observations of non-R&D employees, combined with their expertise drawn from their job. An inventor in our sample who was working in sales in a medical equipment supply company at the time of invention described in his comments on the survey that the idea for the invention came from him observing that his mother was chilled while recovering from surgery. As he left the hospital, pondering this problem (and the lack of solutions in his firm's hospital supply inventory), he started his car and his car seat heater quickly warmed him, giving him the idea for a new device for warming recovering surgery patients. The product has gone through 3 versions and modifications and is used today in the U.S. and foreign countries. Inventions are also created by manufacturing workers doing their normal jobs or from pure inspiration. Examples in our sample include an improved cable connector that performs better in water, and can be adapted across various diameters of cable; a multi-functional headset for aircraft crew members with an emergency oxygen mask and visor unit; and a ballast water treatment system that is both effective and more environmentally friendly than existing systems. Each of these is a new product developed by a production worker and for which their firm applied for patents in the US, Europe and Japan.

4.4.3. Empirical model

The Inventor Survey data provide information about whether an invention is from R&D or non-R&D, given invention. To examine the underlying mechanisms affecting the rates of R&D and non-R&D invention, the probability of R&D invention over the probability of non-R&D invention (i.e. odds) can be decomposed using Bayes' theorem and canceling out the probability of invention from both the numerator and denominator, producing equation 1.

$$\frac{P(RD|invention)}{P(NRD|invention)} = \frac{\frac{P(RD)P(invention|RD)}{P(invention)}}{\frac{P(NRD)P(invention|NRD)}{P(invention)}} = \frac{P(RD)P(invention|RD)}{P(NRD)P(invention|NRD)} \quad (1)$$

Taking the log of the first and last terms in equation 1, we have,

$$\ln\left(\frac{P(RD|invention)}{P(NRD|invention)}\right) = \ln\left(\frac{P(RD)}{P(NRD)}\right) + \ln\left(\frac{P(invention|RD)}{P(invention|NRD)}\right) \quad (2)$$

For the first term in the right hand side (RHS) of equation 2, in general, the non-R&D portion of a firm's activity is larger than the R&D portion. In other words, in most firms, R&D intensity (i.e., the share of employees or sales dedicated to R&D) is relatively small. In fact, mean R&D intensity in U.S. manufacturing (measured as budget share from domestic sales and R&D performance data in BRDIS 2011) is about 3.9% (NSF, 2014), meaning that the average firm invests significantly more effort in "production" than in "R&D". However, given the relative size of R&D and non-R&D in a firm, the base-line productivity (e.g., inventions per person-year or inventions per unit cost) of R&D in inventing will be higher than that of non-R&D because R&D is an activity focused on invention.

Accordingly, the change in the ratio of invention productivity, or relative effectiveness, between R&D and non-R&D (second term in the RHS of the equation 2), controlling for a firm's

relative size of R&D and non-R&D (first term in the RHS of equation 2), will change the ratio of R&D to non-R&D we observe, given invention outputs. Prior studies already analyzed the determinants of the share of R&D in firms or the decision to do R&D (Cohen and Levinthal, 1989), which is not our primary interest. Controlling for the relative ratio of R&D and non-R&D size, we focus on the effect of knowledge environment on invention productivity by R&D and non-R&D (i.e. second-order effects) and hence, the relative probability of observing R&D invention over non-R&D invention. We test the second-order effects of learning by R&D and non-R&D through the unique structure of our data. We take observables that are hypothesized to change the ratio of the probability of invention given R&D activity to the probability of invention given non-R&D activity (last term in equation 2) and show how, controlling for the ratio of R&D to non-R&D activity (first term on RHS of equation 2), changes in these observables (knowledge environment) change the ratios of R&D invention to non-R&D invention (LHS of equation 2) in the expected directions. As an alternative specification, for the multi-invention firms in the sample, we can control for firm-specific characteristics such as management practices as well as the relative size of R&D over non-R&D, using firm-level dummy variables. This will help us see the extent to which nature of knowledge explains the variation in rates of different types of invention, controlling for the mediating effect of firm characteristics (Nelson, 1981).

Based on this model, we use a logit specification to test our hypotheses. In addition, the Inventor Survey used a stratified random sampling procedure (with equivalent sampling rates across strata), and drew randomly one patent per each inventor when inventors have multiple patents, hence each inventor has a different weight. Because of the sampling strategy, the

parameters in all statistics and regression outputs are estimated taking the survey design into account (Kalton, 1983; Lee and Forthofer, 2006).

4.4.4. Variables

The dependent variable is a dummy variable that has 1 for R&D invention and 0 for non-R&D invention using measures described in section 4.2. Therefore, we predict the probability of the invention being R&D invention versus non-R&D invention, not the probability of having an invention or not. In this section, we describe our explanatory and control variables created by multiple datasets.

Importance of general knowledge in industries

The generality of knowledge in the firm's environment is measured by several items. First, more codified knowledge is relatively more generalizable (Arora and Gambardella, 1994; Jensen et al., 2007; Kenney and Dossani, 2005). Using the CMS, the codifiability of knowledge is measured by the industry mean of a 4-point scale asking the importance to the R&D unit of publications and reports a) from other firms or b) from universities or government research labs (the maximum score of two items, one asking about firm sources and the other about universities/government labs): *codifiable knowledge*. Also, if the knowledge is more upstream, it would be more likely to be generalized. The production of basic knowledge in an industry is measured by the industry average percent of basic research produced by **firms** from CMS: *industry basic knowledge*. Finally, university or government lab-driven knowledge can be applied broadly because it is more related to abstract principles. The contribution of university-driven knowledge is measured by the percent of firms in the industry who report that their R&D

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projects in the last three years made use of university knowledge, using the CMS: *university-driven knowledge*. Each characteristic measures an aspect of the generality of knowledge and is not sufficient alone for a proxy for general knowledge. For example, codifying knowledge alone does not necessarily make knowledge more general and accessible to others because using secret codes can undermine transferability (Asheim, 2002; Jensen et al., 2007). Therefore, we create a generality index using the standardized values of these three measures. This index represents industry knowledge characteristics built prior to the time when the firms in the Inventory Survey generate inventions and allows testing the effect of industry knowledge base on the innovation process in firms. The higher value in the index means the more relevance or importance of general knowledge in an industry. Prior work suggests that general knowledge may be more important in high-tech than in low-tech industries (cf. Cohen and Levinthal, 1990; Jensen et al., 2007). Table 4.2A shows the correlation between industry R&D intensity and our general knowledge environment measure. We find they are correlated .32. This correlation is consistent with the interpretation that high-tech industries have higher use of general knowledge, but also with our claim that there can be a second-order effect net of the R&D intensity-general knowledge environment relation.

Visibility of knowledge in industries

Our second measure of knowledge environment is visibility. Visibility is measured with a dummy variable where industries with high visibility of knowledge have 1 and those with low visibility of knowledge have 0. This industry classification, although a coarse measure of visibility, is created from two criteria. First, Stinchcombe (1965) shows that past organizational forms determine the present structure of organizations. For example, the present construction

industry still has aspects of a pre-industrial craft form of organizations, distinguished from more "modern" industries such as chemicals. He classifies industries according to vintage of the establishment of that industry. We argue that following his classification, "prefactory" industries (e.g. printing, ship building, construction, etc.) and "early nineteenth century" industries (e.g. woodworking, glass, leather, apparel, textile, etc.) would likely still have less complex organizational structures, and perhaps also more directly visible production processes, than "modern" industries (e.g., petroleum, chemicals, rubber, electrical equipment, transportation equipment etc.), because the past craft form of organizations is more adapted to problems in that industry (Stinchcombe, 1965). Secondly, as suggested by Seymore (2009), mechanical industries should have higher knowledge visibility, compared to chemical or electronic industries, as illustrated by the contrast between high problem visibility in designing transportation equipment such as motorcycles on the one hand (Sichterman, 2001) and the low-visibility "black-box" semiconductors (except for memory chips), on the other (Owan and Kim, 2013). To determine what industries are more mechanical, we used the CMS and classified industries into two groups: one that has 3-digit NAICS industry means that are above the overall average for the importance of mechanical engineering as a knowledge source, and the other whose means are below average. Using these two criteria (prefactory and early industrial vs. modern; and mechanical knowledge-based vs. other), prefactory/early industries or mechanical knowledge-based industries are grouped into industries with high visibility, and the rest into industries with low visibility. Accordingly, food, textile, wood product, fabricated metal, machinery, computer and electronic product (except semiconductor), transportation equipment, furniture and miscellaneous manufacturing (including medical equipment and supplies) were coded as industries with high visibility (i.e., NAICS 311-316, 321-323, 332-334 (except 3344), 336-339); while chemical,

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pharmaceutical, petroleum and coal, plastics and rubber, non-metallic mineral, metal, semiconductor, and electrical equipment industries are defined as industries with low visibility (i.e., NAICS 324-327, 331, 3344, 335).[16] This classification is displayed in Table 4.2B.

Industry annual growth

Rapidly growing industries can create higher payoff for innovation and increase firms' demand for R&D (Cohen and Walsh, 2000), eliciting relatively more R&D inventions than non-R&D inventions. Therefore, we control for industry average real annual sales growth for 5 years between 1997 and 2002, using U.S. Census data.

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[16] Some may suggest that this high vs. low visibility classification equals low vs. high-tech industries. High-tech/low-tech is based on industry R&D intensity (OECD, 2011). However, we use prior studies of organization structure and technology characteristics and classify high/low visibility deductively. Therefore, our high/low visibility is different from low-tech/high-tech classification. In our classification, the low visibility industry includes several low-tech industries. For example, based on BRDIS 2011 data, R&D intensity of plastics and rubber industry is 1.4%; that of metal industry 0.4%; and that of chemical (except pharmaceutical) industry 1.2%, much lower than the manufacturing mean R&D intensity, 3.9%. Similarly, non-metallic mineral, metal industries are classified into a low-tech industry by OECD (2011), but are included in low visibility in our classification. The high visibility industry also includes high-tech industries. For example, R&D intensity of the computer and electronic product (except semiconductor) industry is 9.9%, greater than the manufacturing mean R&D intensity, and R&D intensity of the machinery industry 3.8%, close to the mean. Moreover, machinery and medical equipment are classified into high-tech industry by OECD (2011), but are included in the high visibility industries by our classification. Overall, the correlation between industry R&D intensity and our high v. low visibility measure is .03 (Table 4.2A). Therefore, our measure is not equal to a low/high-tech classification. We acknowledge there is some measurement error in this measure. For example, as noted above, some segments of semi-conductors (memory chips) have relatively high visibility (Owan and Kim, 2013). Similarly, much contemporary innovation in the food industry is based on chemistry, often with low visibility (Warner, 2013). However, this measurement error would bias our tests toward zero, providing a conservative test of the effects of our visibility hypothesis.

Patent propensity

Since all inventions from the Inventor Survey are patented invention, the effect of patent

propensity needs to be considered. Higher patent propensity in certain units could affect the ratio

of R&D v. non-R&D patented inventions observed in the firm. For example, non-R&D

inventions might have to meet a higher threshold in order to get patented compared to R&D

inventions, which affects the comparison between these two types of inventions. Moreover,

R&D and non-R&D personnel may receive different rewards for invention, which affects

disclosure and patenting of their inventions. Therefore, we control for patent propensity,

measured by what percent of the inventions disclosed by the respondent to her firm resulted in a

patent application, from the Inventor Survey.

Firm size

We control for firm size, which can be associated with cumulative experiences or incentive to

introduce innovation (Cohen and Klepper, 1996a, b; Pavitt, 1984). Firm size is measured by log

of midpoints in categories of employees: less than 100 employees, 100-250 employees, 250-500

employees, and 501 or more employees, from the Inventory Survey.

R&D intensity/Firm dummies

As we discussed in the empirical model (equation 2), controlling for a firm's relative size of

R&D and non-R&D (first term on the RHS of equation 2), we can examine the underlying

relationship between knowledge environment and relative invention productivity by R&D and

non-R&D (second term on the RHS of equation 2), which leads to the change in the ratio of

R&D to non-R&D we observe, given invention outputs. To control the relative size of R&D and

non-R&D in each firm, we use firm size and (disaggregate) industry R&D intensity together. We could not control each firm's R&D intensity due to limitations on firm-level data. We create R&D intensities for assignee firms' NAICS,[17] if possible, at more disaggregate-level NAICS, using R&D funds (except federal funds) and domestic net sales data from the NSF R&D in Industry data in 1999 (NSF, 2002), temporally prior to the Inventor Survey (with inventions from the period of 2000 to 2003), and ran models jointly using this and firm size as a control for firm-level R&D intensity, which together should capture much of the impact of relative size of R&D v. non-R&D units. Because of measurement error in this control for R&D intensity, it is likely that there is some upward bias in our estimates of the effects of knowledge environments.

As an alternative specification, we repeat these tests controlling for assignee firms using firm dummies, to rule out firm heterogeneity and see the extent to which nature of knowledge can explain the variation in rates of different types of invention net of firm differences (Nelson, 1981). In particular, this model controls for differences in R&D intensity and in firm patent propensity, compensating for some of the shortcomings of the first model. However, the model with firm dummies also controls for differences in the relative invention productivity of R&D and non-R&D units due to organizational practices and structures. Furthermore, these firm dummies are likely to capture some of the industry-level knowledge environment effects. Hence, this model is likely to bias downward (toward zero) the effects of knowledge environment on the probability of observing an R&D (v. non-R&D) invention. In other words, the firm dummy controls will mediate some of the impact of knowledge environment on types of inventions

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[17] Firms with multiple businesses were assigned to industry based on the modal industry of the patents assigned to that firm (choosing at random in the case of ties).

observed.[18] Thus, while we suspect that the first model (because of the weak controls for R&D intensity) will overestimate the effects of knowledge environment, the second model will underestimate the effects. Hence, the true effect is likely to be bounded by these two models. For this analysis, we create independent dummy variables for all assignees that have three or more patents in the Inventor Survey data. If we limit the sample to these cases, we have 974 patents representing 121 firms. These patents account for 56% of our sample of patents and these firms represent 15% of the total number of assignee firms in this study sample. However, later, for regression, some observations are omitted, mostly because many firms have only one kind of inventions (i.e. no variation with perfect prediction) and partially due to missing values in other variables. Later in our main regression (Table 4.5), we end up with 444 cases representing 41 firms. The descriptive statistics and correlation matrix of variables are in Table 4.2A.

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[18] Note that the industry of the firm is based on firms' sales, while the industry of the invention is based on the technology class of the invention (and the technology class-industry concordance). Hence, controlling for firms does not completely account for our patent industry knowledge environment variables. To see the degree of collinearity, we regressed our knowledge environment variables on the set of firm dummies used in our models taking survey design into account. We find that the R-squared in the OLS model for generality is .27, and for visibility is .18. Hence, the firm dummies likely capture some of the effects of knowledge environment (more so for generality), but still leaving some independent variance for the direct effect of knowledge environment on the ratio of R&D to non-R&D invention.

Table 4.2A. Correlations

Variable	N	Mean	SD	Min	Max	Correlation								
						1	2	3	4	5	6	7	8	9
1 R&D (vs. Non-R&D) inv	1738	0.88	0.33	0.00	1.00	1.00								
2 Generality of knowledge	1738	0.00	2.32	-3.44	8.34	**0.08**	1.00							
3 Codifiable	1738	0.00	1.00	-3.05	2.46	0.03	**0.71**	1.00						
4 Basic	1738	0.00	1.00	-1.01	4.18	**0.10**	**0.82**	0.35	1.00					
5 University-driven	1738	0.00	1.00	-2.34	1.70	**0.05**	**0.80**	0.29	**0.56**	1.00				
6 Visibility of knowledge	1738	0.57	0.50	0.00	1.00	**-0.10**	**-0.12**	0.02	**-0.35**	0.05	1.00			
7 Industry annual growth	1738	-2.94	2.80	-6.42	6.90	0.04	**0.18**	-0.09	**0.52**	-0.01	**-0.11**	1.00		
8 Patent propensity	1384	68.24	32.44	0.00	100	0.04	0.03	0.02	0.02	0.04	-0.03	-0.01	1.00	
9 Firm size	1738	6.23	0.89	3.91	6.62	0.03	0.00	-0.03	0.02	0.00	**-0.05**	-0.04	-0.05	1.00
10 R&D intensity	1693	6.06	4.42	0.06	32.03	0.02	**0.32**	**0.31**	**0.15**	**0.27**	0.03	-0.03	0.04	**-0.13**

Bold at $p < .05$

Table 4.2B. High vs. Low visible industries

Visibility of knowledge	High	food, beverage, textile, apparel, wood product, paper, printing, fabricated metal, machinery, computer and electronic product (except semiconductor), furniture and miscellaneous manufacturing (including medical equipment and supplies)	NAICS 311-316, 321-323, 332-334 (except 3344), 336-339
	Low	chemical, pharmaceutical, petroleum and coal, plastics and rubber, non-metallic mineral, metal, semiconductor, and electrical equipment	NAICS 324-327, 331, 3344, 335

4.5. Results

4.5.1. Comparing R&D and non-R&D inventions

Based on measures of R&D vs. non-R&D inventions created in section 4.2., Table 4.3 shows that out of all triadically patented inventions, about 12% of inventions are non-R&D inventions. As we described earlier, BRDIS 2011 shows that out of all patented inventions, 6% of inventions are non-R&D inventions (NSF, 2014). However, since BRDIS defines all inventions from R&D performers as R&D invention, BRDIS would underestimate the percentage of non-R&D inventions because it does not distinguish non-R&D inventions from R&D inventions in the R&D performing firms. Our estimate of 12% non-R&D inventions is consistent with this argument. Our project-based measure shows the advantage of using a finer-grained measure of R&D v. non-R&D invention, while still broadly consistent with prior work using the coarser measure. Of these non-R&D inventions in our data, about a third comes from manufacturing units, about 20% comes from sales, service or other units, and the rest comes from R&D sub-units attached to manufacturing, etc. (i.e., technical service), or software development units. These rates of non-R&D invention vary across industries, implying industry-associated characteristics can drive relative differences in the rates of R&D and non-R&D innovation. We can see higher rates of non-R&D inventions in textiles, apparel & leather; wood and paper; fabricated metals; and machinery industries. In contrast, the rates of non-R&D invention are low in food; chemicals; and pharmaceuticals.

Table 4.3. Statistics of non-R&D invention in US manufacturing industries

NAICS		N	NRD Invention % (1)	Non-R&D inventors' work units			
				R&D subunit attached to non-R&D unit (e.g., technical service)	Manufacturing	Software development	Others (e.g., sales)
				(% of non-R&D inventions)			
			(1)	(2)	(3)	(4)	(5)
311-2	Food, beverage and tobaco product manufacturing	5	0.0	0.0	0.0	0.0	0.0
313-6	Textile, apparel and leather	10	21.4	0.0	100.0	0.0	0.0
321-3	Wood product, paper, printing and related support activities	21	20.8	80.0	20.0	0.0	0.0
325	Chemical manufacturing (except pharmaceutical and medicines)	257	4.1	41.7	41.7	0.0	16.7
3254	Pharmaceutical and medicine manufacturing	56	4.5	33.3	33.3	0.0	33.3
326	Plastics and rubber products manufacturing	78	9.1	25.0	37.5	0.0	37.5
327	Nonmetallic mineral product manufacturing	36	11.9	60.0	20.0	0.0	20.0
331	Primary metal manufacturing	16	10.5	50.0	50.0	0.0	0.0
332	Fabricated metal product manufacturing	74	19.5	31.3	50.0	0.0	18.8
333	Machinery manufacturing	266	18.6	42.1	33.3	1.8	22.8
334	Computer and electronic product manufacturing (except semiconductor)	441	12.9	28.4	28.4	16.4	26.9
3344	Semiconductor and other electronic component manufacturing	177	11.7	53.9	23.1	15.4	7.7
335	Electrical equipment, appliance, and component manufacturing	121	11.5	52.9	23.5	11.8	11.8
336	Transportation equipment manufacturing	63	9.5	50.0	37.5	0.0	12.5
337-9	Furniture and related product, and miscellaneous manufacturing	117	14.8	25.0	30.0	5.0	40.0
	All	1738	12.1	38.6	32.1	7.6	21.7

Table 4.4. Descriptive statistics

	Invention type		
	R&D inv (N=1519)	Non-R&D inv (N=219)	t
Invention output			
Product (vs. Process) invention	0.79	0.80	-0.15
Invention process			
No. of information sources (university, customer, supplier etc., max = 11)	5.07	4.47	2.61 ***
Inventor characteristics			
Age at highest degree	28	27	2.21 **
Age at first patent application	34	37	-5.82 ***
Age of first pat app for higest degree=BS	33	37	-2.93 ***
Highest degree = PhD	0.48	0.24	6.66 ***
Highest degree major = Science/Engineering	0.98	0.92	4.60 ***
Value of invention			
Any commercialization (inhouse, start-up, or licensed)	0.53	0.64	-2.75 ***
No. of claims	23.18	22.64	0.47
Forward citation	3.16	3.44	-0.70

*** at .01, ** at .05, * at .10

MBA and JD excluded for comparion of highest degree major

Forward citation as of July 1st 2008

The descriptive analysis of non-R&D and R&D invention in Table 4.4 highlights their similarities and differences. In our sample, about 80% of triadically patented inventions are product inventions and there is no significant difference between R&D and non-R&D inventions in terms of which one is more associated with product invention (p = .90). Therefore, our data mostly represent product invention, allowing a stricter test of our theory, because while much of the literature about non-R&D innovation is about process improvement, we can show that these theories can also explain non-R&D product innovations. Moreover, the descriptive statistics show different characteristics between R&D and non-R&D inventors. First, there is significant difference in number of information sources (e.g., patent literature, conference, universities, suppliers, customers, competitors etc.) used. Non-R&D inventors use fewer sources than R&D

inventors, which is consistent with the claim that non-R&D employees utilize more task-specific knowledge while R&D employees deal with a wider range of solutions or search broadly (Gavetti et al., 2012; Haunschild and Sullivan, 2002; Lüthje et al., 2005; Malerba, 1992; March and Simon, 1958).

Second, R&D employees are usually those who are highly educated, often with a PhD degree; and their role is to search knowledge and develop something from it while non-R&D employees gain more practical knowledge anchored in their normal task. In Table 4.4, we can see that it takes significantly less time for R&D inventors to apply for their first patent compared to non-R&D inventors (mean age 34 vs. 37). Furthermore, age at highest degree for R&D inventors is slightly higher than for non-R&D inventors (28 vs. 27), presumably because of R&D inventors' advanced degree. The rate of inventors with PhD as their highest degree in R&D invention is almost twice as high as that in non-R&D invention (48% vs. 24%). The longer tenure for the first patent for non-R&D inventors suggests that non-R&D employees depend on their accumulated work knowledge more than R&D employees (Kenney and Tanaka, 2003). The rate of inventors with science and engineering as their highest degree is significantly higher in R&D invention than in non-R&D invention, although the majority has S&E degrees in both groups. According to Science and Engineering Indicators 2012 (NSB, 2012), in 2008, 75% of scientists and engineers are employed in non-S&E occupation or S&E related occupation, not pure S&E occupation, which makes it sensible that the majority of observed non-R&D inventors are S&E degree holders. Those non-R&D personnel who have an S&E degree (not necessarily their terminal degree) can combine technical knowledge learned in their education with their experiences in production, sales, and other non-R&D work, resulting in innovations growing out

of their non-R&D activity. This suggests that STEM training, combined with local knowledge, may be an important source of innovative capacity even in the non-R&D units of firms.

Table 4.4 also presents the comparisons of value between the two types of invention: claims, forward citations, and commercialization of the invention (Lerner, 1994; Trajtenberg, 1990). The counts of claims and forward citation between R&D and non-R&D inventions are not significantly different in our sample, while the rate of any commercialization is higher in non-R&D invention than R&D invention. Given that triadically patented inventions have passed a high threshold, and hence are likely to be highly valuable invention, we might not expect major differences between the two groups. However, if we consider the total population of R&D and non-R&D invention including both non-patented and patented inventions, R&D inventions may be relatively more valuable than non-R&D inventions. Yet, what Table 4.4 shows is that there are a significant number of non-R&D inventions that are at least as valuable as firms' R&D invention (cf. Arundel et al., 2008), which can be easily missed by the dominant perspective of innovation research centering on R&D. This table suggests that non-R&D inventions are important beyond the stereotypical image of process improvements or marginal shop-floor inventions.

4.5.2. Nature of knowledge and R&D vs. non-R&D invention

R&D and non-R&D learning generate innovation. However, depending on the characteristics of the knowledge environment where they perform, the effectiveness of learning by R&D and non-R&D can show relative differences, which helps us better understand non-R&D innovation. We first test the effect of different knowledge environments on the relative probability of R&D invention to non-R&D invention. In Table 4.5, column 1 shows that importance of general

knowledge in an environment increases the probability of R&D invention relative to non-R&D invention, while greater visibility of knowledge increases that of non-R&D invention over R&D invention. We also test each indicator of our generality index separately in columns 2 to 4, and the results are robust, with each indicator showing a positive significant effect by itself. If we control the relative size of R&D and non-R&D (i.e., R&D intensity), the predicted ratio of R&D inventions to non-R&D inventions implies the ratio of invention productivity given R&D to that given non-R&D, based on equation 2 above. Using joint controls of firm size and disaggregate industry R&D intensity as a proxy for firm R&D intensity, although allowing some measurement error, the positive effect of importance of general knowledge in column 5 implies that a more general (i.e., less sticky) knowledge environment increases the ratio of the productivity of R&D in inventing to the productivity of non-R&D in inventing, thereby resulting in relatively more R&D inventions being observed than non-R&D inventions, supporting hypothesis 1.

Moreover, the higher visibility of problems affects building and exploiting learning by non-R&D through more problem-solving opportunities in the production process, and results in a relative increase in the invention productivity by non-R&D compared to R&D, given firm R&D intensity, leading to a relative increase in the probability of non-R&D invention being observed rather than R&D invention, supporting hypothesis 2.

Finally, we control for firm-level R&D intensity and other firm-level characteristics, as well as some aspects of firm knowledge environment, using firm fixed effects. Before examining the result of column 7, we test the same model of column 5 for the cases associated with assignee firms having at least three patents to see if there is any selection problem between the full set of cases and those selected cases. Consistent results between column 5 and column 6 show that there is no selection problem. After controlling firm (assignee firm) heterogeneity (column 7),

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the direct effect of general knowledge becomes insignificant (though still positive), implying that the effect of general knowledge on invention productivity is mediated by firm-level characteristics. However, the visibility of knowledge in the invention's industry still has a strong direct effect on relative invention productivity of non-R&D compared to R&D, even after considering mediation by firm-level characteristics. This result implies that higher visibility of knowledge is important to increasing invention productivity of non-R&D even net of individual organizational practices and structures or firm R&D intensity or patentability. Additionally, we aggregated patents to the parent firm-level[19] (not the assignee-firm level) and tested the same model using the parent firm-level dummy variables in column 8. The results between column 7 and column 8 are consistent showing using assignee-level firms or parent-level firms do not make any significant difference. Thus, using, admittedly weak, controls for R&D intensity, we find that knowledge generality and visibility affect the likelihood of observing R&D versus non-R&D inventions. Using, possibly overly strong, controls for firm characteristics, including R&D intensity, we find that firm controls mediate the generality effect, but that the effect of visibility remains. We suspect that the effect of generality is between these two extremes. For controls, the firm size variable by itself is not significant although its direction is positive. Industry annual growth and patentability are positive, but not consistently significant across models.

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[19] We first obtained Compustat identifiers (*gvkey*) for assignee firms in our data, which means, in this process, private firms in our data are excluded. We linked *gvkey* in our data to *gvkey* in the NBER patent database to obtain unique identifiers of company (*pdpco* in NBER), which is more equivalent to parent firms than *gvkey,* which refers to securities (Bessen, 2009).

Table 4.5. Knowledge environment and R&D vs. non-R&D invention

Variables	R&D invention vs. non-R&D invention							
	Logit							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generality of knowledge	0.151 **				0.131 *	0.217 **	0.030	0.069
	(0.065)				(0.067)	(0.109)	(0.104)	(0.097)
Codifiable		0.210 *						
		(0.119)						
Basic			0.433 **					
			(0.183)					
University-driven				0.198 **				
				(0.098)				
Visibility of knowledge	-0.704 ***	-0.713 ***	-0.550 ***	-0.757 ***	-0.730 ***	-0.867 ***	-0.810 **	-0.743 *
	(0.203)	(0.203)	(0.204)	(0.208)	(0.207)	(0.332)	(0.397)	(0.380)
Industry annual growth	0.105 **	0.102 **	0.055	0.088 **	0.115 **	0.124	0.143	0.102
	(0.051)	(0.050)	(0.041)	(0.041)	(0.054)	(0.088)	(0.101)	(0.096)
Inv. patent propensity	0.003	0.003	0.003	0.003	0.004	0.005	0.009 *	0.009 *
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Firm size	0.111	0.113	0.100	0.108	0.107	0.034		
	(0.094)	(0.095)	(0.095)	(0.094)	(0.099)	(0.216)		
R&D intensity					0.007	-0.050		
					(0.023)	(0.041)		
Firm dummies	No	No	No	No	No	No	Yes	Yes
Observations	1384	1384	1384	1384	1353	444	444	477
Model F	F(5, 1379)	F(5, 1379)	F(5, 1379)	F(5, 1379)	F(6, 1347)	F(6, 438)	F(44, 400)	F(47, 430)
	4.11 ***	4.08 ***	3.92 ***	4.31 ***	3.45 ***	2.02 *	1.47 **	1.41 **

*** at .01, ** at .05, * at .10

In addition, we re-defined the visibility variable as a continuous variable only using the industry scores of use of mechanical engineering knowledge and replicated the main model (i.e., columns 5 in Table 4.5) in Table 4.6. We, first, tested each knowledge environment variable separately because of a possible collinearity between two continuous environmental variables measured at the technology industry-level, and replicated the main model. The results basically show that the continuous visibility measure (only considering mechanical engineering knowledge) still shows consistent effects with the dummy measure used in Table 4.5.

Table 4.6. Robustness check with continuous measure of visibility

| Variables | R&D invention vs. non-R&D invention | | |
| | Logit | | |
	(1)	(2)	(3)
Generality of knowledge	0.116 **		0.095
	(0.056)		(0.064)
Use of Mechanical eng.		-1.082 ***	-1.038 ***
		(0.304)	(0.326)
Industry annual growth	0.107 **	0.063	0.082
	(0.047)	(0.042)	(0.052)
Patent propensity	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
Firm size	0.114	0.116	0.110
	(0.098)	(0.098)	(0.098)
R&D intensity	0.004	0.024	0.010
	(0.023)	(0.025)	(0.023)
Firm dummies	No	No	No
Observations	1353	1353	1353
Model F	$F_{(5, 1348)}$	$F_{(5, 1348)}$	$F_{(6, 1347)}$
	2.14 *	4.66 ***	3.18 ***

*** at .01, ** at .05, * at .10

Moreover, out of 1738 patents used in this study, 29% (N=503) has more than one industry assigned in the patent class-product industry concordance. In this case, we randomly sampled one industry. However, to rule out the potential bias by measurement errors from these patents, we also tested the predictions using only patents having one industry in the concordance. Table 4.7 shows that results are consistently significant, in particular, with generality showing even stronger effects than those in Table 4.5.

Table 4.7. Robustness check, limiting to patents having only one industry

| Variables | R&D vs. non-R&D inv | |
| | Logit | |
	(1)	(2)
Generality of knowledge	0.236 ***	0.248 ***
	(0.066)	(0.070)
Visibility of knowledge	-0.667 ***	-0.641 ***
	(0.228)	(0.238)
Industry annual growth	0.197 ***	0.213 ***
	(0.061)	(0.067)
Inv.patent propensity	0.006 *	0.007 **
	(0.003)	(0.003)
Firm size	0.162	0.140
	(0.105)	(0.111)
R&D intensity		-0.018
		(0.026)
Observations	981	958
Model F	F(5, 976)	F(6, 952)
	6.13 ***	5.14 ***

*** at .01, ** at .05, * at .10

Finally, we estimated the models with alternative classifications of R&D and non-R&D invention from our original definition, for example by redefining cases with possible ambiguity in our original classification (e.g. R&D sub-units, or inventions from one's normal non-R&D job but further developed into an R&D project) as R&D invention or excluding those ambiguous cases from the analysis. First, when we redefine all inventions from normal job further developed in an R&D project regardless of work units as R&D invention (columns 1 to 4 in Table 4.8) or excluding all those from the analysis (columns 5 to 8), the results are consistent with those in Table 4.5. Next, when we redefine all inventions from R&D sub-units attached to a non-R&D unit as R&D invention, although some of them are likely to be non-R&D technical service, (columns 1 and 2 in Table 4.9) or exclude all those inventions from the analysis (columns 3 and 4), the results are qualitatively consistent, but losing some significance, mostly in generality of knowledge.[20] To further explore the sensitivity of this category and to decompose the results of columns 1 to 4 in Table 4.9, especially for the reduced effect of generality, we estimate a multinomial probit model with all inventions from R&D sub-units attached to a non-R&D unit (i.e., the highly heterogeneous case that likely includes some R&D and some non-R&D inventions) as a base group. Generality affects the difference between the base group and R&D invention (column 5), but visibility does not have a significant effect. On the other hand,

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[20] Limiting to the cases associated with firms having at least three patents, we also test the models with firm dummies in these classifications. In the models with firm dummies (which capture some of the environmental effects we are testing), the effect of generality becomes close to zero and the effect of visibility stays similar in magnitude but loses significance (likely due to both the substantial decrease in sample size and the measurement error produced by misclassifying the non-R&D inventions from these R&D sub-units). We also test the same models of columns (2) and (4) in Table 4.9 for those selected cases of patents where the assignee firms have at least three patents to see if there is any selection problem between the full set of cases and those selected cases both with firm dummies. We obtained consistent results where only visibility has a significant effect.

visibility affects the differences between the base group and non-R&D invention (column 6), but generality does not have a significant effect. Columns 7 and 8 replicate these results including a control for R&D intensity. These results tell us that invention from R&D sub-units attached to a non-R&D unit has some similarities and differences with R&D invention and non-R&D invention, and suggest that our original definition (including a part of this middle category in R&D invention and a part of it in non-R&D invention based on whether the inventor joins R&D project or not) is a reasonable strategy for dealing with this ambiguity.

Thus, comparing Tables 4.5, 4.8 and 4.9, our results are largely robust to alternative boundaries between R&D and non-R&D invention, although significance levels are sensitive to the specific operationalization of R&D v. non-R&D. We argue that our main operationalization (Table 4.5) is the most consistent with OECD or USPTO definitions. Furthermore, controlling for firm heterogeneity (which captures R&D intensity, firm organization as well as some aspects of knowledge environment) mediates the effect of generality, though the effect of visibility is robust even to this control.

There may be some concern that the non-R&D inventions may be trivial inventions while the R&D inventions are major inventions, making the comparison inappropriate. We note that the R&D and non-R&D inventions in our sample are all triadically patented inventions, which suggests that they have to some degree been filtered based on value. Moreover, in our sample, R&D and non-R&D inventions are not significantly different in forward citations, number of claims, or the probability of being a product (versus process) invention ($p > .10$), which undermines the conjecture that the different characteristics of the types of inventions may be driven by non-R&D inventions being trivial and R&D inventions being important. This similarity in the selection process (leading to triadic patents) produces a more matched sample

for comparison (than if we had data on all inventions from R&D and non-R&D). Hence, if we see significant differences in how each type of invention responds to different knowledge environments, this would be a stronger test of the sensitivity of R&D and non-R&D productivity to differences in the knowledge environment.

Table 4.8. Robustness tests for alternative measures of R&D vs. non-R&D invention, creative process criteria

	Logit							
	All normal job = RDinv				All normal job = .			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generality of knowledge	0.216 **	0.190 **	0.289 **	0.190	0.228 **	0.202 **	0.304 **	0.207
	(0.090)	(0.091)	(0.128)	(0.143)	(0.091)	(0.093)	(0.129)	(0.146)
Visibility of knowledge	-0.557 **	-0.612 **	-0.919 **	-0.979 *	-0.599 **	-0.648 **	-0.905 **	-0.921 *
	(0.261)	(0.264)	(0.398)	(0.509)	(0.264)	(0.268)	(0.409)	(0.527)
Industry annual growth	0.121	0.134 *	0.133	0.126	0.131 *	0.143 *	0.152	0.162
	(0.075)	(0.078)	(0.114)	(0.120)	(0.076)	(0.080)	(0.117)	(0.128)
Inv. patent propensity	0.006 *	0.007 *	0.009	0.010 *	0.006 *	0.007 *	0.008	0.008
	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)
Firm size	0.137	0.162	0.154		0.135	0.158	0.136	
	(0.127)	(0.128)	(0.228)		(0.128)	(0.131)	(0.235)	
R&D intensity		0.016	-0.045			0.013	-0.057	
		(0.032)	(0.057)			(0.031)	(0.058)	
Firm dummies	No	No	No	Yes	No	No	No	Yes
Observations	1384	1353	365	365	1236	1211	328	328
Model F	F(5, 1379)	F(6, 1347)	F(6, 359)	F(35, 330)	F(5, 1231)	F(6, 1205)	F(6, 322)	F(35, 293)
	2.82 **	2.40 **	2.29 **	1.41 *	3.00 **	2.52 **	2.28 **	1.39 *

*** at .01, ** at .05, * at .10

Table 4.9. Robustness tests for alternative measures of R&D vs. non-R&D invention, affiliation criteria

Variables	Logit				Multinomial probit			
	All R&D sub = RDinv		All R&D sub = .		Base group = All R&D sub (to non-R&D) inv			
					RDinv	NRDinv	RDinv	NRDinv
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generality	0.088	0.072	0.096	0.078	0.061 **	-0.001	0.048 *	-0.001
	(0.082)	(0.084)	(0.081)	(0.082)	(0.028)	(0.048)	(0.029)	(0.049)
Visibility	-0.690 ***	-0.714 ***	-0.694 ***	-0.722 ***	-0.018	0.412 **	-0.033	0.418 **
	(0.250)	(0.255)	(0.251)	(0.255)	(0.125)	(0.173)	(0.128)	(0.175)
Annual growth	0.108 *	0.116 *	0.109 *	0.117 *	0.024	-0.043	0.029	-0.044
	(0.065)	(0.069)	(0.065)	(0.068)	(0.022)	(0.037)	(0.023)	(0.038)
Inv. patent prop	0.004	0.005	0.006	0.006	0.004 **	0.001	0.005 **	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Firm size	0.302 ***	0.292 **	0.247 **	0.240 **	-0.290 ***	-0.440 ***	-0.280 ***	-0.424 ***
	(0.101)	(0.107)	(0.102)	(0.109)	(0.076)	(0.090)	(0.078)	(0.092)
R&D intensity		0.000		0.003			0.018	0.015
		(0.029)		(0.028)			(0.015)	(0.020)
Observations	1384	1353	1145	1120	1384		1353	
Model F	F(5, 1379)	F(6, 1347)	F(5, 1140)	F(6, 1114)	F(10, 1374)		F(12, 1341)	
	4.32 ***	3.65 ***	3.80 ***	3.23 ***	4.76 ***		4.25 ***	

*** at .01, ** at .05, * at .10

4.6. Conclusion and implications

We show that both R&D and non-R&D activity generate innovation in an organization, and compare the differences between innovation from R&D to that from non-R&D. Our empirical approach has several differences from prior research. Most importantly, we analyze the R&D/non-R&D distinction at the invention level, which allows for finer-grained analyses of the sources of innovation. Second, we examine inventions at their source, so we do not confound internally and externally sourced innovations. Finally, we are also able to collect multiple inventions from a single firm and use firm fixed-effects models to test the robustness of our models to alternative methods of controlling for R&D intensity, firm strategy and other characteristics. Moreover, given that non-R&D innovation is relatively underexplored in the US, the results of our study are expected to motivate more studies of non-R&D innovation in the US, eventually contributing to the international community of research in this area. We also hope this work will encourage more studies of within-firm variation in innovation rates across units of the firm.

Using these novel data, we show variation in invention-level rates of non-R&D innovation across industries, and further examine these rates by location within the firm (in Table 4.3). Moreover, we compare the characteristics of the two different inventions types, and the two different groups of inventors (in Tables 4.4), to better characterize the profile of non-R&D inventions compared to R&D inventions (among the set of triadically patented inventions). These descriptive data show that non-R&D innovation is not rare (about 12% of all triadically patented inventions), that this rate varies across industries (suggesting industry characteristics may influence the relative likelihood of each kind of invention), and that many of these inventions come from manufacturing, sales or similar functions in the firm. Furthermore, we

show that non-R&D innovations are comparable to R&D innovations in terms of product (versus process) invention and in terms of patent value (citations, claims, commercialization rate). However, the inventors differ significantly (in addition to location in the firm) in terms of age and education (with non-R&D inventors generally older, and R&D inventors more likely to have PhDs and somewhat more likely to have STEM degrees).

Based on prior theory, we expect the diverse internal activities, R&D and non-R&D, in a firm to create innovation through different processes, as each activity has a different competitive advantage for using knowledge with different attributes. Using our unique data, we show when the second-order effects of knowledge environments on rates of innovation by non-R&D increases/decreases relative to that by R&D (controlling for R&D intensity of the firm). The results show that invention productivity of non-R&D increases more than that of R&D the higher the visibility of problems, while invention productivity of R&D is relatively higher in general knowledge environments. This implies that even though two firms have the same ratio of R&D and non-R&D activity, depending on their knowledge environment, they may be relatively more likely to generate one type of innovation than the other.

It is important to note that the Inventor Survey data have some limitations because these data are a subset of inventions and also a subset of U.S. patents, as not all inventions are patented and not all patents are applied for internationally. In the population of all inventions (not limited to triadically patented inventions), non-R&D inventions might be found in even greater rates than what we observe in the Inventor Survey data. However, the data allow us to measure within-firm R&D and non-R&D inventions, which provide distinct measures compared to firm-level measures from the NSF and CIS data. Moreover, the data provide a more matched sample for comparison, allowing a conservative test of our hypotheses. Therefore, if we can see any

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significant difference in our data, the effect may turn out even stronger in the population of all inventions (including non-patented inventions). Thus, our results likely provide insights into what might be considered a lower-bound on the distribution of non-R&D innovations.

This study suggests several follow-on research questions that grow from the limitations. First, future research needs to develop more sophisticated measure of visibility and other characteristics of knowledge, and also analyze values of non-R&D innovation or its participation in the market for technology, not only whether non-R&D activity can generate innovation or not. Our results suggest there may be underexplored high-value non-R&D innovation, unlike common perception that non-R&D innovation is mostly trivial compared to R&D innovation. Next, our goal is estimating the base rate of R&D and non-R&D innovation and also the base rate of second-order learning effects in R&D and non-R&D by variations in the knowledge environments. Given these base rates, future research also needs to explore how a firm's strategy increases or decreases those rates. Future research of R&D and non-R&D innovation in the US can also explore the effect of different external linkages (customers, suppliers, competitors, etc.) or the effect of different market characteristics. Moreover, there is a need for more work in how to build a learning organization by providing training or reorganizing structure to cultivate non-R&D employees' creativity, as well as that of R&D employees (Kenney and Tanaka, 2003; Vallas, 2003). For example, one benefit of such programs as lean manufacturing and similar firm re-engineering is that, not only do they improve quality, but, by making the production process and problems more visible, these organizational innovations should also generate higher rates of non-R&D invention (based on Table 4.5). In addition to organizational restructuring, choices in technology design can make the production process more opaque or more visible (Brown and Duguid, 1991). For example, Noble (1984) documents the choices in the design of numerical

control machine tools that made programming the tools either more or less visible to production workers. Therefore, choices in the development of technology may also affect rates of non-R&D innovation. This perspective also suggests that firms may want to encourage stronger intellectual links between the R&D and non-R&D parts of the firm (Thomas, 1994). Constructing organizational structures that help problems become more visible and provide more learning opportunities, and also organizational policies that encourage employees to disclose their inventions regardless of their work role, and investing in R&D drawing on an understanding of the knowledge environment to increase net value, can all be means to manage innovation more effectively by building learning both from R&D and non-R&D in the firm.

This study has important implications in managing innovation in an organization and developing future innovation policy. First, innovations from non-R&D can be an alternative or complementary strategy to R&D innovations and may have a significant economic value that has been underappreciated. This also means that policies that encourage or allow outsourcing of manufacturing are also facilitating outsourcing of innovation, and, furthermore, that this effect is greatest for high visibility knowledge environments (such as machinery industries). Disentangling different mechanisms for developing learning by R&D and non-R&D activity indicates the importance of non-R&D units as another source for innovation, and guides firm strategy for nurturing the creative potential in non-R&D as well as R&D workforce and developing different types of innovations. Our results highlight the importance of non-R&D innovation for firm and national innovation strategy and suggest the need for developing innovation policies that focus on the non-R&D segment of the economy in order to better tap the large potential for non-R&D innovation. For example, while there may be a general policy goal of encouraging innovation, the policy apparatus of, for example, R&D tax credits specifically

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subsidizes one part of the firm's innovative activity over other parts, although this was not necessarily the intent of the policy. Developing policies that promote innovation more broadly requires recognizing the variation in innovative activity in a firm, and further how that variation is sensitive to differences in the knowledge environments firms face. The importance of non-R&D activity as a resource of innovation varies by industry due to variations in knowledge environments. Hence, understanding the environmental and organizational drivers of non-R&D innovation can help provide a more developed innovation policy and firm strategy. Lastly, patent policy struggles with the definition of "inventor" (see Seymore, 2009). Our work on non-R&D inventions highlights the need for a patent policy that recognizes inventors that develop their inventions outside of formal R&D projects. More generally, this work will ultimately help build a more integrated and nuanced model of the innovation process. These results show that the locus of innovation in the firm is more diffused than the standard R&D-based model suggests. This suggests the need for focus on, training in and recognition of innovation in the rest of the organization, both for managers and for policy-makers trying to track and encourage innovation.

CHAPTER 5

INVENTION NATURE AND MANAGING TECHNOLOGY LICENSES

5.1. Introduction

Research in licensing has grown theoretically and empirically for last several decades. Many studies in licensing have focused on firm characteristics such as size and asset specificity and market characteristics such as competition, appropriability, and market thickness and safety which affect licensing or different stages of the licensing process of firm's new technology or ideas (Agrawal et al., 2014; Anand and Khanna, 2000; Arora and Ceccagnoli, 2006; Conti et al., 2013; Fosfuri, 2006; Gambardella et al., 2007; Gans and Stern, 2003; Gans and Stern, 2010). In addition, some studies deal with knowledge characteristics embedded in technology (e.g., tacit knowledge) and licensing strategy (Arora, 1995; Teece, 1981). However, firms may produce multiple inventions which have different characteristics and need different strategies for licensing. This provides opportunities for studying how firms strategize for licensing those different inventions which are generated from different activities in a firm or associated with different information. New technologies or ideas can be generated by formal R&D projects, but also by relatively more localized and downstream activities such as technical service, manufacturing, marketing and sales activities in a firm. Inventions generated from those different activities within a firm should be managed differently, considering licensing revenue and rent dissipation. Therefore, firms may have to differentiate their strategy to match invention characteristics.

For structuring licensing management in a firm, Arora, Fosfuri and Rønde (2013) (hereafter, AFR) model the different ways to organize licensing activity in a firm: centralization,

decentralization, and hybrid form, focusing on differences in information and differences in incentives. They theorize that while decentralization, or licensing decision by a (risk-neutral but credit-constrained) business unit, enjoys superior information about licensing opportunities but has lower licensing incentive because of rent dissipation exceeding licensing revenue, centralization, or licensing decision by a (risk-neutral) headquarter, increases incentive for licensing with monetary benefits, independent of (business unit) private benefit. A hybrid structure maximizes licensing with large licensing deals directly managed by the top management and smaller licensing deals delegated to the business unit. The model predicts that inventions characterized by more or less direct competition between licensor and licensee (e.g., inventions from R&D vs production/practice) will be associated with different ways to manage licensing (Arora et al., 2013). Their theoretical model also suggests additional predictions on the relationship between technology characteristics in terms of the range of application and the degree of transferability and licensing activities: firms will centralize licensing for general-purpose technologies because those technologies creates less rent dissipation with the less direct competition between licensor and licensee. However, these predictions have not been tested empirically. This chapter builds on the AFR model and tests the implications of their main arguments in terms of inventions with different characteristics --- origins of invention (i.e. R&D vs. non-R&D activities) and output technology characteristics (i.e. general-purpose vs. specific-purpose) --- which they argue should be assigned to the different parts of organization or best managed by different structure (e.g., centrally vs. decentrally), with invention-level licensing data. Moreover, the further implication of the AFR model is examined in terms of restrictions on the licensing contract. Differences in incentives from the tradeoff between rent dissipation and licensing profits on invention are related to the different level of risk between potential licensors

and licensees, which affects the strength of restriction on the licensing contract (Somaya et al., 2011; Williamson, 1983). Therefore, combining the AFR model with hostage theory, this chapter analyzes how inventions from diverse internal activities (i.e. R&D vs. non-R&D) and with the different level of technology generality are associated with different licensing terms to reduce potential risks.

This study provides empirical evidence of the relationship between invention associated with different organizing of licensing and licensing activity controlling for market and firm features using novel invention-level licensing data from a survey with broad industry coverage. These survey data provide multiple variables related to the licensing activity complementing and validating one another and producing results supporting the main arguments driven by the theories. Furthermore, more strict tests are conducted by controlling for industry dummies to rule out possible industry characteristics (e.g., including industry demands for licenses as well as industry competition, growth, and appropriability regimes), which provides benefits of controlling for both industry supply and demand of licenses. The results suggest that firms need different strategies for different inventions generated internally. Invention characteristics are important to the firm's decision to join the licensing market and the negotiation for reducing potential risks between licensors and licensees.

5.2. Theories and hypotheses

5.2.1. Origins of invention and incentive to license

When firms face the moment of decision whether or not they are willing to license, they will consider the net balance between rent dissipation effect and licensing revenue effect to make a decision. When revenue from licensing payments is larger than reduction in market share, firms

will supply their technology as well as the product (Arora and Fosfuri, 2003; Fosfuri, 2006). The difference in net balance between rent dissipation and licensing revenue may vary by structure of managing licensing. The AFR model proposes that decentralization of licensing (i.e. delegation of authority to business units) is associated with lower incentive to license than centralized structure because business units prioritize sales or market share, relatively more influenced by production-based incentives, which makes licensing costlier. This implies that inventions managed by centralized structure should be more likely to join the licensing market because firms are more willing to license those inventions with monetary benefits from licensing less concerned about direct rent dissipation.

According to the AFR model, inventions with different characteristics are best managed by different parts of the organization associated with different level of incentive to license (i.e. centralized vs. decentralized licensing). Inventions from R&D, which has potential economies of scope but uncertain returns to business units, are best managed by the centralized unit whereas inventions from production or practice activities, or outside of R&D (e.g., production, marketing, sales, and technical service), depend on local information and are more attached to business units or decentralized structure (Arora et al., 2011; Arora et al., 2013; Kay, 1988). Therefore, the AFR model deduces the following prediction of licensing incentives for inventions from upstream and downstream activities:

H1: Firms are more willing to license inventions from R&D activities than inventions from non-R&D activities.

5.2.2. General-purpose invention and incentive to license

The other characteristic of invention related to different management is whether or not the invention is general-purpose technology, and according to the AFR model, firms will centralize licensing for general-purpose technologies. Note that inventions from R&D activities are not always general-purpose inventions because characteristics of input can be different from characteristics of output. Technologies in invention generated have different characteristics in terms of the range of application and the degree of transferability. General-purpose technologies have a broad scope of application and the lower costs of general use, and are more transferable across sectors of the economy (Aghion et al., 2002; Bresnahan and Gambardella, 1998; Rosenberg and Trajtenberg, 2004), "opening up new opportunities rather than offering complete final solutions" (Bresnahan and Trajtenberg, 1995). Therefore, general-purpose technologies are characterized by less closeness to the market and less direct competition between the licensor and the licensee (Arora et al., 2013). Since firms may not have capabilities to fully use the general-purpose technologies, those with inefficient production techniques for the technology may be willing to find the licensee who has better commercial capabilities (Gallini and Winter, 1985; Rothaermel, 2001). Moreover, inventing firms can expand the use of invented technology for different applications and enter the different market, licensing it to other firms which may not be their direct competitors, thereby accruing relatively stronger rewards for licensing than those for product market profits (Aghion et al., 2002; Arora et al., 2013; Arora and Gambardella, 2010; Bresnahan and Gambardella, 1998; Teece, 1981). Based on these characteristics of general-purpose technology, the AFR model predicts that firms will centralize licensing for general-purpose inventions, and it leads the following testable hypothesis:

H2. Firms are more willing to license general-purpose inventions than specific-purpose inventions.

5.2.3. The centrality of licensing management and licensing terms

The licensing market is imperfect due to the limited number of sellers and buyers, opportunistic behavior of licensors and licensees, and uncertain returns from the deal (Caves et al., 1983). In this imperfect market, licensors and licensees have double-sided moral hazard problems. The licensor may be concerned about losing control of the technology to their licensee, raising a potential competitor because once the licensee learns, it is hard to "unlearn", increasing risks from the licensee's capabilities unknown at the time of the deal (Arora, 1996; Somaya et al., 2011). On the other hand, the licensee may worry that the licensor could allow the limited exposure to its actual operations, not willing to provide sufficient information to understand the technology, and renegotiate the contract, making valueless the licensee's technology-specific investments that are made on the uncertain prospect of a licensed technology and have limited alternative applications (Arora, 1996; Caves et al., 1983; Somaya et al., 2011). The licensee will not undertake technology-specific investments without assurance of adequate returns for their investments (Gallini and Wright, 1990). Therefore, these double-sided hazards can be mitigated by posting a hostage to support exchange and promote cooperative relationships, for example, by providing exclusivity in the licensing alliance (Poppo and Zenger, 2002; Reuer and Ariño, 2007; Somaya et al., 2011; Williamson, 1983). The contractual hostages through exclusivity will reduce the licensee's concern about hold-up risk and the licensor's giving the technology to rivals. For the licensor, the exclusivity provision may limit her freedom. However, if the licensor lacks assets for exploiting the technology, and if the assets are not readily acquirable through

alternate partners, then she will more likely grant exclusivity (total or partial) in exchange for the licensee's investment in technology specific capabilities. In other words, the exclusive licensing is payment by the licensor for the licensee's investment in capabilities for exploiting the technology and for fully developing and commercializing the invented technology.

Centralized and decentralized units can react to risks from these hazard problems differently. For example, decentralized units, which are closer to the market, will be concerned about the hazard problem more than centralized units because they are directly related to market share and production profits. Therefore, the different level of risks on licensing inventions managed by different structures should be considered in negotiating and structuring the licensing agreements, or creating contractual hostages between licensor and licensee. Transferring technologies often requires the transfer of know-how, which is costly and demands close interaction between licensor and licensee. For example, Arora (1996) illustrates an example that the transfer of chemical process technology requires face-to-face training or technical services involving a variety of issues such as how to store chemicals, control the production process, and handle unscheduled breakdown. Through this close interaction, the licensee undertakes more targeted investments, which increases the licensee's risk if the licensor makes an alliance with another partner (Somaya et al., 2011). Moreover, because inventions from production and practice or inventions including more specific technologies, which are more decentralized for licensing management, are characterized by more direct competition in the market, the licensee can be a competitor eroding the licensor's market share. This makes the licensor more likely restrict the product or geography scope in the licensing contract for which the licensee can apply the technology (Arora et al., 2013; Somaya et al., 2011). For these reasons, firms will be less willing to license those inventions so that they are less likely to join the licensing market (H1 and

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H2). However, once inventions join the licensing market, inventions by decentralized licensing will be more likely to have exclusivity clause on the licensing contract than those by centralized licensing because not only does the contract need to give the licensee incentives to take a risk on investing in specialized capabilities, but also control their competitor to minimize rent dissipation from licensing. This leads to the following hypothesis:

H3a. Firms will be less likely to engage in exclusive licensing for inventions from R&D activities than those from non-R&D activities (given the licensing deal).

H3b. Firms will be less likely to engage in exclusive licensing for general-purpose inventions than specific-purpose inventions (given the licensing deal).

5.3. Data and methods

5.3.1. Data

The focal data in this study are from the US Inventor Survey. The Inventor Survey is a survey of US inventors on triadic patents (patents filed in Japan and the EPO and granted by the USPTO) in the application period 2000 to 2003, and collects information on the projects and licensing activity at the year of 2007. The survey sampled triadic patents stratified by NBER technology classes, and to select one patent per inventor, randomly drew one patent out of multiple patents belonging to the same inventor. The number of patents belonging to each unique inventor was recorded to use as a weight for later survey data estimation. The survey received 1919 responses with a response rate of 24.2% (31.9% adjusted for undelivered, deceased, etc.). After limiting data to patents assigned to firms (i.e., excluding universities and hospitals, government labs and individual inventions), the sample used in this study includes 1738 triadic patents. Several

variables created from Carnegie Mellon Survey (CMS) (Cohen et al., 2000), and US Census data

are merged into the Inventor Survey data. The CMS is a survey administered in 1994 of R&D

managers in R&D units located in the US conducting R&D in manufacturing industries as part of

a manufacturing firm, and includes information on appropriability regime. The US Census

provides industry sales data prior to the Inventor Survey. To combine those data, industry

concordances are created among the three datasets building from the US Census SIC-NAICS

concordance between CMS and US Census and the USPTO US patent class-product industry

NAICS concordance between Inventor Survey and US Census data.[21] Therefore, industry

variables for the invention represent the characteristics of the industry that is related to the

patented technologies. Industry dummies are also used to control for industry characteristics

more strictly for robustness tests.

5.3.2. Empirical model

While most studies about licensing investigate whether the technology is licensed, some studies

elaborate their analyses considering the different stages of the licensing process (Agrawal et al.,

2014; Gambardella et al., 2007). Agrawal et al. (2014) operationalize the three stages of the

licensing process: the stage of identifying potential licensors and licensees, the stage of

negotiation, and the stage of agreements reached, and find that market thickness and market

safety are important for the first and the last stage respectively while bargaining frictions affect

licensing deal failure in the middle stage. Gambardella et al. (2007) analyze when there is

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[21] Some patent classes have multiple relevant product industries. In this case, we randomly sample one industry.

willingness to license and when the technology is actually licensed given willing to license. Given the separate stages of willing to license and being actually licensed given willing to license, however, this study focuses on the stage of willing to license and tests the effect of different licensing activity on the probability of joining the licensing market using a probit model. Moreover, the tests of licensing exclusivity are conducted by a probit model to predict the probability of having exclusivity given the licensing deal, and, alternatively, a multinomial probit model including those not licensed given willingness to license.[22] However, when the sample is limited to only those licensed for the probit model or only those that are willing to license for the multinomial probit model, the random variability of sample selected is considered with the original survey design. Therefore, standard errors in the models of selected sample are estimated using the unconditional, full population because subpopulation sizes (i.e. those licensed, or those willing to license) within strata are random and the true subpopulation size is not known, and needs to be estimated in the full population (West et al., 2008).

5.3.3. Variables

Dependent variables

Willing to license

Building on the European inventor survey by Giuri et al. (2007), the US Inventory Survey distinguishes the incentive to license from the actual license deal, asking three different categories of licensing: 1) licensed, 2) not licensed but willing to license, and 3) not licensed.

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[22] The best model which reflects the structure of data would be sample selection multinomial probit model, which estimates the selection equation for willing to license and the outcome multinomial model given the selection, but not supported by existing statistical software (Miranda and Rabe-Hesketh, 2006).

Willing to license is a dichotomous variable taking 1 if the patent-hold is willing to license (including the case of actually being licensed) and 0 if the patent-holder is not willing to license (i.e. not licensed).

Licensed

The variable takes 1 if it is actually licensed and 0 if the patent is not licensed (including not licensed but willing to license). This variable will be used given willing to license or without any limitation depending on specification.

Licensing exclusivity

This is a dichotomous variable taking 1 if the licensing contracts include exclusivity clauses and 0 if they do not include exclusivity clauses. Only respondents who have licensed the patent are supposed to report this.

Explanatory variables

Invention from R&D activities (vs. non-R&D activities)

Inventions created from organized R&D projects or employees doing R&D are more associated with centralized licensing while inventions from non-R&D activities such as production, technical service, sales and marketing are more associated with decentralized licensing (Arora et al., 2011; Arora et al., 2013). Using questions about the creative process in producing the invention and the inventor's affiliation within a firm collected from the Inventor Survey, the variable of inventions with different origins is created.

The question about the creative process is as follows:

Which of the following scenarios best describes the creative process that led to your invention?

a. The **targeted achievement** of a research or development project

b. An **unexpected by-product** of a research or development project

c. An **expected by-product** of a research or development project

d. Directly **related to your normal job** (which is not inventing), and was then further developed in a (research or development) project

e. From **pure inspiration/creativity** or from your normal job (which is not inventing), and was not further developed in a (research or development) project

The inventors' affiliation is categorized by the following units:

1. An independent R&D unit or its sub-unit

2. R&D sub-unit attached to a unit with its primary focus on non-R&D such as manufacturing

3. Manufacturing

4. Software development

5. Other (e.g. Sales/marketing)

The inventions from (a, b, c) OR (1) are coded as invention from R&D. This implies that for example, even though the inventor's affiliation is in the manufacturing unit, if she joins the creative process of a, b, or c, the output invention is considered invention from R&D activities because the invention is created by an official R&D project. On the other hand, inventions from (d, e) AND (2, 3, 4, 5) are coded as invention from non-R&D activities. If invented ideas are originated by workers who are not in an independent R&D unit and do not join the centrally

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organized R&D projects, those ideas will relatively more depend on local information. Note that

R&D sub-units attached to non-R&D spend substantially more effort on technical service than

those from independent R&D units or its sub-unit (14% v. 7%, p < .01 in the Inventor Survey

data). Therefore, when workers in R&D sub-units attached to non-R&D do not join the

organized R&D projects, they are more involved in technical service. It is hard to draw a clear

line between inventions from R&D activity and inventions from more production- or practice-

based activity, or outside of R&D activity. However, this ontological framework with contrasts

in invention types will be useful to understand the relationship between the level of centrality in

organizing licensing and the firm's licensing activity in the market.

General-purpose invention (vs. specific-purpose invention)

General-purpose invention has a broad range of applications. Patent scope is used as a proxy for

generality of invention because broader patent scope represents the larger number of domains or

applications covered by it (Gambardella et al., 2007). It is measured by the log of the number of

claims and the log of the number of IPCs (Lerner, 1994). Claims and IPCs include different

features. First, claims are built by patent applicants. Patent applicants list as many claims as

possible to increase their invention's coverage, and claims include relatively detailed, applied

explanation in different settings. Later, patent examiners finalize claims, either accepting all or

narrowing down to some if another patent already is covering the same application. However,

IPCs are assigned by patent examiners and show technology areas to which the invention may

apply, but not explanations of the application of the technology. Therefore, claims and IPCs are

distinct ways to measure the scope of invention, and both are used for the analyses. Table 5.1

shows that these two measures are uncorrelated. For IPCs, 3-digit IPCs are used because the

change of the number of aggregate-level IPCs represents more substantial change of scope. Four-digit IPCs are also used for the additional tests, but do not change the results.[23]

Controls

Firm size

We control for firm size because it could be related to bargaining power in licensing negotiation, complementary assets, market shares or different ways to use alliance (Fosfuri, 2006; Gambardella et al., 2007; Gans and Stern, 2003; Rothaermel and Boeker, 2008). Firm size is categorized into large firms (>500), medium firms (100-500), and small firms (<100, reference group) based on the number of employees, from the Inventor Survey.

Any external co-inventor

Having external co-inventors can affect the chance of licensing. Therefore, the analysis controls for existence of external co-inventor. About 11 % of triadic patents have an external co-inventor (see Table 5.1).

Industry annual growth

Rapidly growing industries can create higher payoff for innovation and increase firms' demand of new technologies (Cohen and Walsh, 2000). Therefore, the analysis controls for industry average real annual sales growth for 5 years between 2002 and 2007, from US Census data.

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[23] Results are available from the author.

Competition

Competition in the market for technology could increase or decrease the incentive to license. While the larger number of potential suppliers of a technology creates a strategic incentive to license, it can decrease the rate of licensing because the number of buyers is limited and high competition attenuates the revenue effect (Arora and Fosfuri, 2003; Fosfuri, 2006). Competition is measured by industrial average of technology competitors from CMS (Cohen et al., 2000).

Appropriability

Strong intellectual property rights can reduce the sellers' concern about losing their property rights (Anand and Khanna, 2000; Arora and Gambardella, 2010). Strong IP not only has a traditional role of creating monopoly, but also opens the market for technology trade (Gallini and Winter, 1985). Therefore, the analysis controls for industrial scores of *patent effectiveness*. However, patent and secrecy can be used simultaneously to secure appropriability, in particular if the technology includes know-how, and thus are not mutually exclusive. Moreover, firms may depend on different mechanisms at the different stages in the innovative process (Levin et al., 1987). While firms can strongly rely on secrecy in the early stage of the process, patent can become more important in the later stage after completing innovation, preventing others not in technology trade from imitating easily by reverse-engineering (Arundel, 2001). Therefore, we also control for *secrecy effectiveness* together with patent effectiveness, both of which are from CMS (Cohen et al., 2000).

Filed year

We control for patent application years.

NBER Technology classes

We also control for technology classes, which are related to product differentiation more than firm characteristics and, thereby, related to likelihood of licensing (Arora and Fosfuri, 2003; Fosfuri, 2006).

Industry dummies

Industry variables introduced above mostly control for the supply-side characteristics. Arora et al 2010) point out that the attention to technology markets in prior studies has been lopsided to the supply of technology, for example, appropriability regime, downstream assets, firm size and market competition. However, given the supply of technologies needed, potential buyers may underinvest in external technology, inefficiently developing internally because of "Not Invented Here" syndrome and deterrence of competition to their internal innovation, which causes tension between buying and making technology (Arora and Gambardella, 2010). Therefore, to control more strictly for both supply and demand-side characteristics of industry which can affect the incentive to license, and to examine the effects of invention characteristics more clearly, industry dummies are used for further tests. *Furniture and related products and miscellaneous manufacturing* is used as the reference group (for industry classification, see Table 5.2). The descriptive statistics of all variables are displayed in Table 5.1.

Table 5.1. Summary statistics

Variable	N	Mean	SD	Min	Max	Correlation											
						1	2	3	4	5	6	7	8	9	10	11	12
1 Willing to license	1356	0.30	0.46	0	1	1.00											
2 Licensed	1356	0.13	0.34	0	1	**0.59**	1.00										
3 Licensing exclusivity	113	0.68	0.47	0	1	--	--	1.00									
4 R&D (vs. non-R&D) inv	1738	0.88	0.33	0	1	0.05	0.02	**-0.17**	1.00								
5 Log(no. of claims)	1738	2.93	0.70	0	5.20	**0.07**	0.02	0.12	-0.01	1.00							
6 Log(no. of IPCs)	1738	0.10	0.26	0	1.61	-0.01	-0.01	0.13	-0.03	0.00	1.00						
7 Large firm (>500)	1738	0.81	0.39	0	1	**-0.09**	**-0.10**	**-0.25**	0.02	**-0.06**	-0.01	1.00					
8 Medium firm (100-500)	1738	0.07	0.26	0	1	-0.05	-0.02	-0.03	0.02	0.00	-0.01	--	1.00				
9 Any external co-inventor	1610	0.11	0.31	0	1	-0.02	0.01	0.11	0.02	-0.01	**-0.05**	**-0.07**	0.02	1.00			
10 Industry annual growth	1738	5.59	4.32	-4.05	15.14	**0.11**	0.04	0.02	-0.01	**0.07**	**-0.10**	-0.03	0.00	-0.01	1.00		
11 Competition	1738	3.71	0.70	2.52	5.83	**0.10**	0.05	0.15	**0.09**	0.01	**0.07**	-0.02	0.04	-0.03	**0.11**	1.00	
12 Patent effectiveness	1738	35.02	7.82	17.83	53.31	**-0.10**	-0.04	0.06	-0.02	**-0.08**	**0.13**	**-0.08**	0.05	0.04	**-0.40**	**-0.09**	1.00
13 Secrecy effectiveness	1738	49.36	4.54	41.40	60.15	-0.05	-0.01	-0.01	**0.08**	**-0.06**	**0.14**	0.01	0.01	-0.01	**-0.59**	**0.17**	**0.48**

Note: Correlation with bold numbers at $p < .05$

5.4. Results

5.4.1. Descriptive statistics

Licensing activity varies by industry because of different characteristics associated with industry (e.g. competition, market thickness). Table 5.2 shows industrial statistics of the licensing-related variables: *willing to license*, *licensed*, and *licensing exclusivity*. Out of the responses to the licensing question in the sample, 30% are willing to license. Food and beverage (331-2), chemical (325), pharmaceutical (3254), primary metal (331), computer (334), semiconductor (3344), and electrical equipment (335) manufacturing industries have high percentage of willing to license, above the overall mean. Out of those that are willing to license, about 43% are licensed, which means about 13% in total (also see Table 5.1). Pharmaceutical (3254) and Computer (334) have high percentages of being licensed out of willing to license and also in total. Moreover, more than half of licensing deals have exclusive clauses. Across industries, exclusivity in the licensing deal is very high in food and beverage (331-2), wood product and printing (321-3), nonmetallic mineral product (327), and primary metal manufacturing (331).

The rates of willing to license are significantly different across industries, while those of being licensed given willing to license and engaging in exclusive licensing given license are not significantly different across industries (Table 5.2). However, the latter two statistics are estimated by relatively few responses (for being licensed or not given willing to license (N = 397), and having exclusivity or not given license (N = 113)), and so it may be difficult to see significant differences in this sample. Later we will see some conditional effects from industry characteristics, controlling for firm and invention characteristics.

Table 5.3 explains the similarities and differences of invention from R&D activities and that from non-R&D activities. In the sample, about 80% of triadically patented inventions are product inventions and there is no significant difference between invention from R&D activities and that from non-R&D activities in terms of which one is more associated with product invention (t= -.15; p = .90). Therefore, the data mostly represent product invention. Moreover, the descriptive statistics in Table 5.3 show differences and similarities in other invention and inventors' characteristics between invention from R&D activities and that from non-R&D activities. First, there is significant difference in number of information sources used, with invention from non-R&D activities created from less sources than invention from R&D activities, which is consistent with the attribute by definition that invention from non-R&D activities should be associated with more localized knowledge. Second, employees who are involved in organized R&D are usually those who are highly educated, often with a PhD degree; and their role is to search knowledge and develop something from it while employees doing downstream activities such as production, sales, and technical service gain more practical knowledge anchored in their normal task. In Table 5.3, we can see that it takes significantly shorter time for inventors conducting R&D activities to apply for their first patent than for

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inventors conducting non-R&D activities (or context-specific inventors) (34 vs. 37), although age at highest degree for R&D inventors is slightly higher than for inventors working outside of R&D (28 vs. 27) presumably because of R&D inventors' advanced degree. The rate of inventors with PhD as their highest degree in invention from R&D activity is almost twice as high as that in invention from outside of R&D (48 % vs. 24 %). Most inventors' highest degree (excluding MBAs and JDs) is from science and engineering in both groups. However, the rate of inventors with science and engineering as their highest degree is significantly higher in invention from R&D activities than in invention from non-R&D activities. Lastly, it may be easily misunderstood that inventions from R&D activity are general-purpose inventions. However, inventions from R&D activity can include either general-purpose technologies or specific-purpose technologies. Table 5.3 shows that there is no significant difference between invention from R&D activity and that from non-R&D activity in generality of output technology. Therefore, origin of invention (R&D vs. non-R&D) and output technology characteristics (general-purpose vs. specific-purpose) are separate measures, showing different aspects of invention.

Table 5.2. Statistics of licensing by industry

NAICS		N	(1) Willing to lic (%)	(2) Lic|Willing (%)	(3) Exclusive|Lic (%)
311-2	Food, beverage and tobaco product manufacturing	5	40.0	50.0	100.0
313-6	Textile, apparel and leather	10	0.0	n.a	n.a
321-3	Wood product, paper, printing and related support activities	21	25.0	20.0	100.0
325	Chemical manufacturing (except pharmaceutical and medicines)	257	31.5	39.5	68.4
3254	Pharmaceutical and medicine manufacturing	56	33.3	55.6	85.7
326	Plastics and rubber products manufacturing	78	24.6	50.0	50.0
327	Nonmetallic mineral product manufacturing	36	25.0	50.0	100.0
331	Primary metal manufacturing	16	37.5	33.3	100.0
332	Fabricated metal product manufacturing	74	24.3	38.9	85.7
333	Machinery manufacturing	266	20.9	39.6	55.6
334	Computer and electronic product manufacturing (except semiconductor)	441	32.2	46.0	65.7
3344	Semiconductor and other electronic component manufacturing	177	49.3	38.9	60.0
335	Electrical equipment, appliance, and component manufacturing	121	35.1	30.0	77.8
336	Transportation equipment manufacturing	63	27.4	70.0	38.5
337-9	Furniture and related product, and miscellaneous manufacturing	117	22.6	46.2	90.9
	All	1738	30.1	42.8	67.6
	Industry difference test		$F_{(13, 1346)}$ 2.11**	$F_{(13, 1737)}$ 0.68	$F_{(9, 1609)}$ 0.93

*** at .01, ** at .05, * at .10; F statistics adjusted by the survey design

Table 5.3. Comparison between invention types

	Origin of invention		
	R&D (N=1519)	Non-R&D (N=219)	t
Invention output			
Product (vs. Process) invention	0.79	0.80	-0.15
Invention process			
No. of information sources (university, customer, supplier etc., max = 11)	5.07	4.47	2.61 ***
Inventor characteristics			
Age at highest degree	28	27	2.21 **
Age at first patent application	34	37	-5.82 ***
Highest degree = PhD	0.48	0.24	6.66 ***
Highest degree major = Science/Engineering	0.98	0.92	4.60 ***
Technology characteristics: General purpose			
Log(no. of claims)	2.93	2.94	-0.31
Log(no. of IPCs)	0.09	0.11	-1.07

*** at .01, ** at .05, * at .10; MBA and JD excluded for comparion of highest degree major.

IPCs at 3 digits

5.4.2. Centrality of licensing and incentive to license

Following ARF, both inventions from R&D and General-purpose inventions are managed by the centralized unit. Therefore, firms will be more willing to join the licensing market with inventions from R&D activities and general-purpose inventions through centralized licensing (Aghion et al., 2002; Arora et al., 2013). Column 1 in Table 5.4, first, shows the results with a probit model of willingness to license. Column 1 shows that firms are more willing to license inventions from R&D activities, supporting Hypothesis 1. Column 1 also presents that firms are more willing to license general-purpose inventions, supporting Hypothesis 2. However, it is only significant for the measure by log of number of claims, not the measure by log of number of IPCs. To control for industrial characteristics more strictly, Column 2 estimates the probit model with industry dummies, which possibly control for industry demand of license and other industry characteristics as well as industry annual growth, competition, and appropriability regimes. Therefore, industry characteristic variables are excluded when controlling for industry dummies. The controls of NBER technology classes are also excluded because industries are already defined by patented technologies. The result in 2 is consistent with that in column 1. Next, column 3 displays the result of the probit estimation to determine the probability to license ignoring willingness to license. None of the explanatory variables are significant, which corroborates that invention characteristics are more related to the stage of willing to license (i.e., incentive). For controls, firm size has still negative significant effects in this model, consistent with the findings in Gambardella et al. (2007). Higher product differentiation in the market increases competition with licensing and thereby larger profit dissipation, making the firm less willing to even enter the licensing market (Fosfuri, 2006). Patent effectiveness does not have any special effect on licensing of patented inventions, which is consistent with the findings in Arora

and Ceccagnoli (2006) that patent effectiveness has a direct effect on patenting payoffs and licensing payoffs, but not on licensing payoffs given patent. Columns 4 to 6 show the results of OLS models and the results are consistent.

Table 5.4. Invention types and licensing activity

Variables	Probit			OLS		
	Willing to lic (1)	Willing to lic (2)	Licensed (3)	Willing to lic (4)	Willing to lic (5)	Licensed (6)
R&D (vs. non-R&D) inv	0.283 **	0.238 *	0.127	0.084 **	0.071 **	0.026
	(0.123)	(0.121)	(0.153)	(0.036)	(0.036)	(0.028)
General-purpose						
Log(no. of claims)	0.110 *	0.123 **	0.035	0.036 **	0.042 **	0.006
	(0.059)	(0.060)	(0.071)	(0.019)	(0.019)	(0.014)
Log(no. of IPCs)	0.030	0.002	-0.017	0.011	0.002	-0.001
	(0.154)	(0.156)	(0.178)	(0.050)	(0.052)	(0.036)
Large firm (>500)	-0.543 ***	-0.501 ***	-0.531 ***	-0.191 ***	-0.180 ***	-0.126 ***
	(0.113)	(0.112)	(0.130)	(0.042)	(0.042)	(0.037)
Medium firm (100-500)	-0.726 ***	-0.721 ***	-0.530 ***	-0.249 ***	-0.250 ***	-0.126 ***
	(0.176)	(0.176)	(0.198)	(0.056)	(0.057)	(0.046)
Any external co-inventor	-0.083	-0.092	0.016	-0.026	-0.029	0.000
	(0.123)	(0.123)	(0.146)	(0.039)	(0.040)	(0.030)
Industry annual growth	0.035 **			0.012 **		
	(0.014)			(0.005)		
Competition	0.232 ***			0.073 ***		
	(0.073)			(0.023)		
Patent effectiveness	-0.010			-0.003		
	(0.007)			(0.002)		
Secrecy effectiveness	0.019			0.006		
	(0.014)			(0.004)		
Filed year dummies	Yes	Yes	Yes	Yes	Yes	Yes
NBER Tech classes	Yes			Yes		
Industry dummies		Yes	Yes		Yes	Yes
Observations	1257	1250	1250	1257	1257	1257
F test	$F_{(19, 1238)}$ 3.91 ***	$F_{(23, 1227)}$ 2.75 ***	$F_{(23, 1227)}$ 1.80 **	R2 0.07	0.06	0.03

*** at .01, ** at .05, * at .10

5.4.3. Centrality of licensing and exclusivity of licensing

Inventions associated with decentralized licensing, which are inventions from non-R&D activity or specific-purpose inventions, may increase risks for licensors and licensees relatively more than inventions by centralized licensing because of high risk on licensors for losing their market share and high risk on licensees for uncertainty of contract after their targeted investments. This elicits higher exclusivity in the licensing contract for inventions managed by decentralized licensing than inventions managed by centralized licensing. Column 1 in Table 5.5 shows that inventions from R&D activity lower the probability of having exclusivity clauses in the licensing contracts while we cannot see the same relationship between general-purpose inventions and exclusivity, partially supporting Hypothesis 3. The results are consistent after controlling for industry dummies in column 2. For the further analysis, the multinomial probit model (which relaxes the independence assumption of the error terms and hence the IIA property which is easily violated by multinomial logit) is run with three categories: no licensing (reference group), licensing with non-exclusivity clauses, and licensing with exclusivity clauses, for those that are willing to license. Columns 3 and 4 present that invention from R&D activity significantly increases the probability of licensing with non-exclusivity clauses over non-licensing. Additionally, in the multinomial probit model with industry dummies in columns 5 and 6, the significance of inventions from R&D activity gets weaker, not significant at the conventional level (although p-value is about .15). However, it has no significant effect on the probability of licensing with exclusivity clauses over non-licensing although the direction is negative. These results are consistent with the argument in Hypothesis 3a. However, there is no significant relationship between general-purpose invention and exclusivity, not supporting Hypothesis 3b.

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Table 5.5. Invention types and licensing exclusivity

Variables	Probit Exclusivity (1)	Probit Exclusivity (2)	Multinomial probit (ref = not licensed but willing) Lic with no exc (3)	Lic with exc (4)	Multinomial probit (ref = not licensed but willing) Lic with no exc (5)	Lic with exc (6)
R&D (vs. non-R&D) inv	-1.770 ***	-1.271 *	1.212 *	-0.309	0.912 †	-0.181
	(0.628)	(0.647)	(0.664)	(0.409)	(0.633)	(0.383)
General-purpose						
Log(no. of claims)	0.342	0.099	-0.206	0.079	-0.166	-0.035
	(0.250)	(0.226)	(0.204)	(0.170)	(0.202)	(0.162)
Log(no. of IPCs)	0.686	0.425	-0.757	0.040	-0.670	0.140
	(0.714)	(0.614)	(0.508)	(0.400)	(0.523)	(0.396)
Large firm (>500)	-0.633 *	-0.936 **	-0.255	-0.887 ***	-0.129	-0.961 ***
	(0.356)	(0.368)	(0.355)	(0.286)	(0.340)	(0.275)
Medium firm (100-500)	-1.623 **	-1.191 *	0.652	-0.319	0.408	-0.648
	(0.659)	(0.627)	(0.694)	(0.571)	(0.696)	(0.557)
Any external co-inventor	0.164	0.308	0.305	0.723 **	0.208	0.564 *
	(0.437)	(0.414)	(0.404)	(0.342)	(0.411)	(0.323)
Industry annual growth	0.000		-0.041	-0.044		
	(0.048)		(0.044)	(0.043)		
Competition	0.056		-0.180	-0.038		
	(0.346)		(0.280)	(0.218)		
Patent effectiveness	-0.067 *		0.039	-0.010		
	(0.036)		(0.027)	(0.022)		
Secrecy effectiveness	-0.111 *		0.100	-0.059		
	(0.059)		(0.067)	(0.042)		
Filed year dummies	Yes	Yes	Yes	Yes	Yes	Yes
NBER Tech classes	Yes		Yes	Yes		
Industry dummies		Yes			Yes	Yes
Observations	103	98	322		322	
F test	F(18, 1648)	F(18, 1573)	F(38, 1625)		F(34, 1629)	
	2.13 ***	1.92 **	103.31 ***		121.37 ***	

*** at .01, ** at .05, * at .10; † p =.15

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The measures of general-purpose invention by claims and IPCs may have limitations to capture the characteristics of general-purpose technology or may better represent other characteristics of the invention. In particular, a broad patent scope, defined by the number of IPCs, may be associated with the high value of the patent (Lerner, 1994). If the generality of technology is also associated with high value, firms may be less willing to license general-purpose inventions and further more willing to put exclusivity clauses when licensing although it is managed by centralized licensing. This may make the relationship between general-purpose inventions and willing to license or exclusivity unclear in the models. Moreover, although general-purpose inventions are characterized by less direct competition between licensor and licensee, they may be sometimes better managed by decentralized licensing because application of general-purpose technology requires "innovational complementarities", that is, "the interplay between a bundle of improved technological attributes that characterize the general-purpose technology and the wider environment (e.g., downstream application sectors or geographical locations) in which the general-purpose technology operates (Rosenberg and Trajtenberg, 2004)". If general-purpose invention is managed by centralized licensing, the relationship between general-purpose technology and its users may depend more on arms-length market transactions, which would produce "'too little, too late' innovation in both the general-purpose technology and the application sectors (Bresnahan and Trajtenberg, 1995)". However, the decentralized unit (e.g. business unit), through their relatively more embedded business relationships or geographical market information, may have better information of potential users which can innovate and improve their own technologies using the general-purpose technology. Therefore, it is likely that general-purpose invention is not only associated with centralized licensing because of the wide range of applications, transferability, and less direct competition between licensor and licensee,

but also associated with decentralized licensing because of innovational complementarities. These complicated characteristics on general-purpose technology may make the relationship between general-purpose invention and licensing activity more ambiguous.

5.5. Conclusion and implications

Building on and extending existing research on market- and firm-level drivers of licensing activity, this study, based on the AFR theoretical model, uses invention-level licensing data to examine how inventions managed by different structures are related to different strategies in the licensing process and advances research on the relationship between contractual exclusivity and relational governance. First, the results show that invention origin (R&D vs. non-R&D activity) and output characteristics (general-purpose vs. specific purpose) are related to the firm's incentive to join the licensing market. More specifically, inventions from R&D activity are more likely to engage in the licensing market than inventions from non-R&D activity. Also, there is some evidence that general-purpose inventions are more likely to engage in the licensing market than specific-purpose inventions. While many existing studies on licensing have analyzed what characteristics of firms affect the firm's licensing rate or what industrial characteristics drive more licensing activity of the firm, moving beyond this approach, this study analyzes how firms build a licensing strategy for different inventions, which is not uniform. Furthermore, the data are not limited to a particular industry, such as chemicals or pharmaceuticals. The results show the effects from data spanning all manufacturing industries, providing more comprehensive analyses. Looking at internal strategic dynamics in firms across industries through invention-level analysis adds new evidence on the effects of invention characteristics on licensing

strategies and outcomes, contributing new results to the field of strategic management of licensing.

This study also considers the process of structuring agreements, highlighting differences due to inventions with different licensing management, adding new empirical evidence to the AFR theoretical model and to research on contractual structure in licensing deals. Inventions by centralized and decentralized licensing face different levels of hazard problems in the licensing market. The results show that inventions from non-R&D activity are more likely to have exclusivity clauses than inventions from R&D activity because inventions from non-R&D activity need relatively more hostages due to higher risks for both licensors and licensees. However, this does not hold for specific-purpose inventions (vs. general-purpose inventions). Therefore, the results partially support that inventions managed by decentralized licensing are more likely to have exclusivity clauses in the licensing deals. Further study is needed to develop better measures and also develop a more elaborate theory of general-purpose technology to test the relationship between general-purpose technology and licensing activity more clearly. Because general-purpose technology requires "innovational complementarities", we may not be able to simply argue that it is managed by centralized licensing, which requires a more careful theory of managing general-purpose technology. Moreover, future research should include non-patented inventions as well as patented inventions for analysis based on the evidence that a substantial rate of non-patented inventions joins the market for technology (Cockburn and Henderson, 2003). Despite these limitations, this study provides empirical evidence of the AFR model, contributes to better understanding the strategic management of licensing and markets for technology, and suggests more research opportunities beyond firm- or market-level analyses of licensing.

CHAPTER 6

IMPLICATIONS AND CONTRIBUTIONS

This dissertation begins by comparing different innovation indicators, introduces non-R&D innovation into research on innovation, and then analyzes characteristics of non-R&D inventions as well as the different impacts of non-R&D and R&D invention on the decision to participate in markets for technology. These results allow us to elaborate discussion about how to improve measurement of innovation, overcome the limited view of innovation research focusing on R&D, and develop several arguments related to firm innovation strategy and performance, improving our understanding of the innovation process and helping innovation policymakers depend more on solid scientific findings on innovation.

The comparison of existing innovation indicators guides us to considering the understudied area of non-R&D based innovation. The study of non-R&D innovation contributes to better tapping innovation management and policy understandings of the organizations of innovation to create a more balanced view of the innovation system and capture the neglected economy. Considering non-R&D innovation is especially important for policy. For example, current policy such as R&D tax credits (generated from the R&D-centered view in innovation policy) consequently subsidizes one kind of innovation, R&D innovation, although this may not be what this policy actually intended. While innovation from R&D has been assumed to have more spillover effects than that from other activities (and hence is worth of subsidy), this is an empirical question. However, even assuming that R&D has more spillover effects, it is not always better. What we want may be the limited spillover effects within country, not across countries or all over the world because we still want to keep our competitive advantage. In this

sense, broader spillover effects by R&D-driven technologies cannot always be considered better than relatively narrower spillover effects by non-R&D-driven technologies. Rather, non-R&D-driven technologies may spill over across units within a firm or across agents within a region, bringing the moderate spillover effects but still keeping the region competitive.

Firms have different internal capabilities for conducting R&D and different productivity of R&D. Non-R&D-based innovations can be an alternative (and complementary) strategy to R&D-based innovations and may have a significant economic value that has been under-appreciated. Thus, organizations may underuse innovation-potentials based on the conventional perception that innovation is generated by R&D. However, activity outside of R&D does not simply respond to the results of R&D but may also suggest product innovation, so that experience in and understanding of production and practice processes outside of R&D can open new product possibilities (Thomas, 1994). Furthermore, although the rates of generating innovation outside if official R&D will vary by knowledge environment in which those non-R&D activities operate, workers outside of R&D can also create new solutions and new products on their own, based on learning by production at commercial scale and their own experiments, often unobserved by others. This viewpoint is consistent with recent policy discussions emphasizing the importance of production in the US innovation economy. For example, outsourcing a manufacturing function overseas is a prevalent strategy by US firms. However, for some industries or some firms, outsourcing manufacturing may mean outsourcing innovation itself. Policy decisions or business decisions regarding this outsourcing need to be made with careful consideration of different external knowledge characteristics and importance of cumulative work experiences for innovation, in addition to short-term production cost reduction. Training employees in non-R&D as well as R&D is also important to cultivate their potentials to

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generate innovation. Some states provide training for their residents to attract more manufacturing facilities in their states. A good example is Georgia's Quick Start workforce training program attracting KIA auto factory through this way (Dobbs, 2013). This dissertation further suggests that training manufacturing employees beyond their minimum skills and avoiding strict work authority between R&D and non-R&D would promote innovation potentials also from the other side of the organization. Not only training, but also building more visible organization structures (e.g., TQM, lean manufacturing) will increase the rate of non-R&D innovation, thereby increasing overall innovativeness in the organization.

Lastly, the research on willingness-to-license of non-R&D and R&D invention will move current research on licensing, which mostly focuses on firm and market characteristics, one step forward, elaborating the effects of inventions associated with different organizing of licensing on the firm's licensing activity in the market for technology. The results suggest that firms may have to differentiate their strategy to suit invention characteristics, contributing to the field of strategic management of licensing.

Overall, this dissertation tries to answer the more fundamental question in the science of science and innovation policy on the understanding of the nature of knowledge in the innovation process and the likely outcomes of inventions embedding different characteristics. I believe, this research broadens understanding of innovation in organizations and leverages this broader understanding in order to develop our theories of innovation and improve the empirical foundation for innovation policy.

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