Selling University Technology: Patterns from MIT

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Many research universities engage in efforts to license inventions developed by university-affiliated inventors. However, no systematic explanation of the conditions under which university inventions will be licensed or commercialized has been provided. Drawing on transaction cost economics, I provide a conceptual framework to explain which university inventions are most likely to be licensed, commercialized, and generate royalties, and who will undertake that commercialization. I test this framework on data on the 1,397 patents assigned to the Massachusetts Institute of Technology during the 1980–1996 period. The results show that (1) university inventions are more likely to be licensed when patents are effective; (2) when patents are effective, university technology is generally licensed to noninventors; (3) when patents are effective, licensing back to inventors increases the likelihood of license termination and reduces the likelihood of invention commercialization; and (4) the effectiveness of patents increases royalties earned for inventions licensed to noninventors. The implications of these findings for innovation management and strategy, entrepreneurship, and university technology commercialization are discussed.

(*Entrepreneurship; Contracting; Patents*)

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1. Introduction

Recent years have witnessed rapid growth in university technology licensing activity and supporting institutional arrangements. From 1980 to 1997, the number of universities licensing technology has grown eightfold, to over 200 (Thursby and Kemp forthcoming). From 1991 to 1996, the number of university licensing agreements has grown by 70%, and the real dollar value of royalties has doubled (Association of University Technology Managers (AUTM) 1997. Moreover, many universities have adopted specific policies and procedures to encourage technology licensing, including rules on information disclosure, consulting arrangements, royalty payments, and equity investments. Several universities (e.g., Iowa State University) have even incorporated technology licensing into their strategic plans.

However, this university technology licensing activity has occurred in the absence of any systematic explanation of which university inventions will be licensed and commercialized or who will conduct that commercialization. This absence of information is surprising since researchers have recognized that approximately half of all university patents are never licensed, and that licensing activity is not randomly distributed across patents (Jensen and Thursby 2001, Hsu and Bernstein 1997, Barnes et al. 1997).[1]

In this paper, I draw on the transaction cost economics literature to identify the conditions under which university technology will be successfully licensed and commercialized. I argue that university inventions are more likely to be licensed when patents are an effective mechanism for appropriating the returns to innovation because the patent system

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[1] For example, universities seem to be better at finding licensees and earning royalties in the biological rather than the physical sciences (Thursby and Kemp forthcoming).

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reduces the transaction costs of technology transfer. When patents are ineffective, university technology is likely to be licensed back to noninventors because inventor commercialization mitigates the information problems that plague markets for inventions.

When patents are effective, licensing to noninventors reduces the likelihood of license termination, and increases the likelihood of invention commercialization, by allowing commercialization to be undertaken by economic actors who possess a comparative advantage in that activity. As a result, the effectiveness of patents in a line of business will increase the royalties earned for inventions licensed to noninventors.

I test these arguments by examining (1) the hazard rate of licensing for the population of 1,397 patents assigned to the Massachusetts Institute of Technology (MIT) from 1980 to 1996, (2) the probability that the licensee of the 717 licensed patents will be a noninventor, (3) the hazard rate of license termination and invention commercialization for the population of 966 patent-licensing efforts[2] between 1980 and 1996, and (4) the royalties paid to MIT for the 167 patents licensed to noninventors from time of license through 1997.

Examination of university technology licensing from a contracting perspective is valuable for three reasons. First, universities are increasing their efforts to license technology. A framework that explains which inventions will be successfully licensed and commercialized provides insight into the conditions under which universities will be able to use licensing as a mechanism to earn financial returns. Second, the application of a contracting perspective to university technology licensing yields useful implications for the literature on innovation strategy and management by providing insight into the licensing and self-commercialization of inventions. Third, the transaction cost framework provides valuable implications for the entrepreneurship literature by explaining the conditions under which inventors will become entrepreneurs.

The article proceeds as follows: The next section draws on theories of contracting to provide a conceptual framework that explains why patent effectiveness should influence university technology licensing. The third section describes the context for the study. The fourth section describes the study's methodology. The fifth section presents the results. The sixth section provides a discussion. The final section draws implications for related literatures.

2. Appropriability, Contracting Costs, and the Licensing of University Technology

The best solution for university technology commercialization requires that economic actors who have a comparative advantage in that activity commercialize the technology. On average, the inventors of university technology do not have a comparative advantage in technology commercialization. Technology commercialization involves a set of skills—including identifying customer needs, developing product concepts, designing products and processes, prototyping, and manufacturing—that university inventors rarely possess.

The superiority of other parties at the commercialization of university inventions generates opportunities to gain from trade (Pisano and Mang 1993). In the absence of problems in markets for knowledge, the licensing of inventions to those advantaged in technology commercialization provides a mechanism for allocating inventions to those actors who are best able to commercialize them (Teece 1980).[3] Trade, in turn, increases the returns from technology commercialization. The division of the surplus that results from the more efficient use of resources makes both parties

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[2] There are more "licensing efforts" than licensed patents because "licensing efforts" examine each attempt by a firm to license a patent, and some patents are licensed by more than one firm.

[3] The skills necessary for successful technology commercialization are largely tacit and are developed through a process of learning-by-doing (Teece 1981). As a result, these skills are not sold effectively in markets (Teece et al. 1997). Therefore, if invention and technology commercialization are combined through market-mediated transactions, this combination will result from the sale of inventions to economic actors with a comparative advantage in technology commercialization, rather than the sale of technology commercialization skills to economic actors with a comparative advantage in invention.

better off than if university inventors commercialized technology in an autarkic manner.

The solution described above is contingent on the effective functioning of markets for inventions. However, three information problems—adverse selection, moral hazard, and hold-up—prevent markets for inventions from working effectively. Adverse selection occurs when opportunistic sellers of low quality inventions misrepresent the quality of their inventions as high quality because potential buyers cannot easily discern the value of inventions (Anton and Yao 1994). Moral hazard occurs when the parties to the transaction shirk on the provision of inputs to the technology transfer process because the ability to verify their provision is low (Arora 1996). Hold-up occurs when the parties to the transaction opportunistically renegotiate the terms of the technology transfer agreement to take advantage of specific investments made by the other side (Pisano 1989).

Adverse selection exists in markets for inventions because these markets are plagued by disclosure problems. To minimize adverse selection, Arrow (1962) explained that buyers are unwilling to pay for knowledge unless the value of that knowledge can be demonstrated. However, demonstration requires the seller to disclose her knowledge; and once the invention has been disclosed, the buyer has no incentive to pay for it (Anton and Yao 1994).

Moral hazard exists because third parties cannot verify effectively the quality and quantity of knowledge transfer. The buyer may refuse to pay for knowledge that has been transferred since she cannot be forced to unlearn the transferred knowledge (Arora 1996). At the same time, the seller may shirk on the transfer of knowledge to economize on its cost (Arora 1995).

Hold-up exists because the commercialization of technology is inherently uncertain, markets are thin, and complete contracts cannot be written (Pisano 1991). As a result, both sides are obliged to leave some subjects open for future negotiation. However, these agreements to "agree in the future" provide an incentive for both parties to opportunistically renegotiate the terms of the agreement after the other side has made a relationship-specific investment (Pisano 1989, p. 114).

The use of patents reduces adverse selection, moral hazard, and hold-up problems in technology transfer. Patent protection mitigates adverse selection by reducing the disclosure problem (Arrow 1962). The possession of a patent allows the seller to disclose an invention to a potential buyer while retaining the property rights to the invention after disclosure. If the disclosure convinces the buyer that the invention has value, patent protection will force the buyer to pay for the invention if she wants to use it (Anton and Yao 1994).

The use of patents also minimizes moral hazard. Patents allow at least some dimensions of the quality and extent of knowledge transfer to be verified effectively by third parties, minimizing the incentive for shirking (Anand and Khanna 2000). Moreover, when patents protect the codified components of a transferred invention, the enforcement of patents can be used as a bargaining tool to ensure that parties do not engage in moral hazard with respect to uncodified components (Arora 1996).

Finally, patents minimize the potential for hold-up. When information is codified in patents, it can be made less ambiguous, and contracts governing its transfer can be made more complete (Teece 1981). More complete contracts reduce the threat of hold-up by mitigating the potential for ex-post haggling over unspecified terms. In contrast, when information is tacit, it must be transferred through interpersonal contact, and economic actors must develop relationship-specific assets to facilitate that transfer (Pisano 1991). This approach raises the potential for hold-up. Because parties to a transaction cannot take back relationship-specific assets used to facilitate the transfer of knowledge, the parties will lose the value of sunk relationship-specific investments if an agreement is terminated (Williamson 1975). As a result, the parties become locked into the transaction, increasing the potential for opportunistic renegotiation of the agreement (Pisano 1989).

Since patents reduce the information problems inherent in markets for inventions, patented university inventions should be licensed relatively easily. However, in practice, the effectiveness of patents varies significantly across technologies (Mansfield 1981). In some fields, patents can be invented around at low cost, whereas, in others, they provide strong protection for their duration (Teece 1986). Patents are less effective when they are unlikely to be held valid if challenged, if firms cannot enforce them, if competitors can legally "invent around" patents, if the technology is moving so fast that patents are irrelevant, if patent documents require disclosure of too much proprietary information, if licensing is required by court decisions, or if firms participate in cross-licensing agreements with competitors (Levin et al. 1987).

Given the importance of patents in mitigating failure in markets for inventions, the effectiveness of patents in a line of business should encourage university technology licensing. Some prior work provides initial support for this idea. In case studies of 14 inventions licensed from MIT and Harvard University, Hsu and Bernstein (1997) found that firms were more interested in licensing in sectors in which patents provided a strong competitive advantage. Similarly, Barnes et al. (1997) found a significant effect on licensing for a patent effectiveness control variable in their study of license and citation patterns for University of California patents. This argument leads to the first hypothesis:

HYPOTHESIS 1. *The greater the effectiveness of patents in a line of business, the greater the likelihood that university inventions in that line of business will be licensed.*

The above argument also suggests that when patents are effective, the best solution to technology commercialization is possible: University inventions will be sold to the economic actors best able to commercialize the inventions. As explained, on average, parties outside of universities have a comparative advantage in commercializing technology. Therefore, when patents are effective in a line of business, university technology will be licensed primarily to noninventors, and noninventors will be more successful at commercializing that technology.

However, when patents are ineffective, markets for knowledge do not work effectively. Under these circumstances, the second-best solution—inventor commercialization—will occur. To reduce the adverse selection, moral hazard, and hold-up problems that plague markets for inventions, inventors will found firms to commercialize their own inventions. If the inventor commercializes her own technology, disclosure problems, the incentive for moral hazard, and hold-up are mitigated (Teece 1980). This argument leads to the following hypotheses:

HYPOTHESIS 2. *The greater the effectiveness of patents in a line of business, the greater the likelihood that the licensee of a university invention will be a noninventor.*

HYPOTHESIS 3. *The greater the effectiveness of patents in a line of business, the greater the likelihood that university inventions licensed by inventors will be abandoned prior to commercialization.*

HYPOTHESIS 4. *The greater the effectiveness of patents in a line of business, the lesser the likelihood that university inventions licensed by inventors will reach commercialization.*

HYPOTHESIS 5. *The greater the effectiveness of patents in a line of business, the greater the magnitude of royalties generated from licenses to noninventors.*

3. The Context: Technology Licensing at the Massachusetts Institute of Technology

This paper explores the licensing of MIT-assigned patents over the 1980–1996 period. I focus on MIT's patents over this timeframe because both the institutional context and the time period are useful for explaining university technology licensing. The focus on MIT mitigates bias that might result from the investigation of new entrants into technology licensing. Although the first university technology licensing efforts took place at the University of California at Berkeley and the University of Chicago, MIT was one of the earliest universities to establish a formal technology transfer organization (in 1932). Moreover, MIT is the most important source of university technology creation in the United States. The top 20 universities patent approximately 70% of all university patents, and MIT alone accounts for approximately 8% of the total (Henderson et al. 1998).

The focus on the leading university patent generator provides several advantages for this study. First, high patenting universities generate higher quality inventions (Henderson et al. 1998), which are more likely to be licensed. By exploring MIT's patents, I can explore licensing in a university with a relatively even distribution of licensed and unlicensed patents. Second, high patenting universities are more likely to receive significant private sector interest in their inventions. This level of interest reduces the likelihood that licensing is explained by idiosyncratic factors, which may explain licensing at universities where the level of patenting is too low to warrant formal scanning by private firms. Third, by focusing on the highest patenting university, the study is able to draw conclusions about an institution that has a significant impact on private sector economic activity even if generalization cannot be made to other settings.[4]

Furthermore, MIT's policies provide a good setting for a natural experiment to determine which inventions are licensed. Unlike many universities (e.g., Columbia University and the University of California) that will not patent an invention until the licensing office has identified a licensee, MIT will patent inventions on speculation.[5] The policy of making the patenting decision before the licensing decision mitigates sample selection bias that would hamper investigation of licensing at universities that do not patent unless they have already identified a licensee.

The examination of technology licensing in the post-1980 timeframe is also valuable. The year 1980 marked a watershed in university technology licensing. Before 1980, the property rights to all federally funded inventions resided with the federal government. Although universities could apply for patents on inventions resulting from federally funded research, they had little incentive to do so. In the pre-Bayh–Dole era, universities could earn income from those patents only if they received a title rights waiver from the government agency funding the research (Henderson et al. 1998). Consequently, prior to 1980, few universities engaged in technology licensing, and the volume of licensing was quite limited.

In 1980, Congress passed the Bayh-Dole Act, which gave universities the rights to income from inventions that resulted from federally funded research (Henderson et al. 1998). Moreover, in 1984, Congress expanded these rights with Public Law 98-620, which increased the range of inventions from which universities could profit, and the ease with which they could transfer those property rights. The transformation of university property rights in the post-Bayh–Dole era makes investigation of this period important.

4. Methodology

Sample and Analysis

The first part of this study investigates the 1,397 patents made by faculty, staff, and students of the Massachusetts Institute of Technology (MIT) between 1980 and 1996 and subsequently assigned to the institute. In this analysis, I use Cox proportional hazard duration models to examine the hazard of first license.[6]

The second part of the study examines who (inventors or noninventors) were the licensees for the population of 717 patents licensed between 1980 and 1996. In this analysis, I use logistic regression to examine the probability of license by a firm not founded by any of the inventors.[7]

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[4] Unfortunately, I have little information on technology licensing from other universities on which to compare MIT. Although the fraction of MIT inventions that have been licensed may "seem high," no information on the cross-university proportion of patents that are licensed is publicly available. However, one variable that is available (for 122 universities from 1991–1998) is the ratio of license and option agreements executed to patents issued. On this measure, MIT is not significantly different from the mean at the $p < 0.05$ level.

[5] Personal correspondence with Lita Nelsen, director, and Lori Pressman, associate director, TLO.

[6] Duration models are designed to incorporate information on both cases for which an event of interest has occurred and those for which an event has not yet occurred, correcting for the effects of censoring. Because I make no claims about the functional form of time dependence, the Cox model offers the best approach to modeling time dependence.

[7] In unreported regressions, I also examine the probability that the licensee will be a firm founded by one of the inventors. Because some of the patents were licensed by inventors and noninventors, the two operationalizations of the dependent variable are not inverse. However, the results are qualitatively the same (support the same argument at similar levels of significance with similar magnitudes) when the dependent variable to be predicted is license to inventors.

The third part of the study examines the population of 966 efforts to commercialize licensed MIT patents between 1980 and 1996. In this analysis, I use Cox proportional hazard duration models to examine the effect of the interaction of patent effectiveness and inventor-licensee on both the hazard of cancellation of the license to the patent and the hazard of first sale of products and processes in which the invention is embodied.

The fourth part of the study examines the royalties generated from the population of 167 MIT patents commercialized between 1980 and 1997 by noninventors. In this analysis, I use Tobit regression to explore the relationship between patent effectiveness and the dollar value of the royalties generated from commercialized inventions.[8]

Dependent Variable: Licensing

To measure licensing, I examined the MIT Technology Licensing Office (TLO) records of its licensees. I constructed annual spells, which begin when a patent is issued and end when a patent is first licensed. The variable was coded 1 if the TLO records revealed that a patent was first licensed in that year, 0 otherwise. Patents that were not licensed during the observation period were treated as censored. Of the 1,397 inventions in the sample, 51.3% were licensed.

Dependent Variables: Inventor Licensees

I examined the TLO records to identify the entity that licensed the 717 licensed patents. The licensees were coded "noninventor" if the entity was a firm that was not founded by any of the inventors listed on the patent. I predict the probability of license to noninventors.

Although inventors could become involved in licensee firms by serving on the scientific advisory boards or as consultants to the new ventures, I examine firm founding rather than these alternative forms of involvement for four reasons. First, consulting and advisory board membership do not represent the construct of entrepreneurship as defined in the prior literature, whereas firm founding does. Consequently, examining the likelihood of license to ventures not founded by inventors allows comparison of the findings to prior literature on entrepreneurship. Second, firm founding captures the effect of equity ownership of new ventures. The transaction cost literature on which I build focuses on the concept of ownership by a single party as a solution to contracting problems. Inventor involvement through arrangements that do not necessarily involve equity ownership, such as scientific board membership or consulting, does not capture this core construct. Third, the empirical test that I undertake requires the determination of inventor involvement with the patented invention at the time of license. Because consulting arrangements and scientific advisory board membership are often established after the time of license, their measurement in this context is problematic. Fourth, I analyze data at the level of the invention, not at the level of the firm. Because consulting arrangements and scientific advisory board memberships are firm-level constructs, they are difficult to operationalize at the level of analysis at which I examine the data.

Dependent Variable: License Termination and First Sale

After patents are licensed, the licensee can terminate the license to the patent at any time. I measure the hazard of termination. Technology licensing officers at MIT explain that licensees typically terminate licenses because they cannot make the technology work in a cost-effective manner, because their strategic plans change, because the company does not want to continue to pay license fees, or because they have changed the product or business that they are developing so that the intellectual property is no longer useful.[9]

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[8] Tobit regression measures the effect of independent variables on changes in the dependent variable when the distribution of the dependent variable is truncated. Because I wish to draw inference about the relationship between patent effectiveness and royalties received by MIT for a distribution in which commercialized patents generate royalties greater than zero, Tobit regression is appropriate. However, I obtain substantively the same results with ordinary least squares regression.

[9] Personal correspondence with Lita Nelsen, Director, and Lori Pressman, Associate Director, TLO.

To measure license termination, I constructed annual spells, which begin when a patent is first licensed and end when the license agreement's coverage for a patent is terminated. The variable was coded 1 if TLO records revealed that the license agreement coverage for a patent was terminated in that year, 0 otherwise. Licensed patents that were not terminated during the observation period were treated as censored. Of the 966 patent-licensing efforts in the sample, 33.4% were terminated.

After patents are licensed, commercialization of the invention also can occur at any time. To measure commercialization, I constructed annual spells, which begin when a patent was licensed and end when a product or process using the licensed patent first generated revenues through sale to another company. The variable was coded 1 if the TLO records revealed that a first sale occurred in that year, 0 otherwise. If a product or process using the licensed patent did not achieve a first sale during the observation period, the patent was treated as censored. Of the 966 patent-licensing efforts in the sample, 20.4% were embodied in products or processes that reached a first sale.

Dependent Variable: Royalties

To measure royalties, I examined the dollar value of the nonequity royalty payments made to MIT from sales of products that employed licensed patents through 1997 for the 167 inventions that had been commercialized by noninventors. (Option fees, patent maintenance fees, sublicense revenues, and one-time fees are not included in these figures.)[10] I used the TLO records of its royalty receipts to construct this variable. Since the royalty receipts are highly skewed, I predict the log of the royalty figure.

Yale Measures

To measure the effectiveness of patents in a line of business, I constructed a "patent effectiveness" scale from the Yale Survey on innovation. In that study, Levin et al. (1987) surveyed technology managers from different lines of business about technological change in their line of business.[11] The respondents served as line of business experts rather than as company representatives, and answered a variety of Likert-style questions about their line of business. Their answers were averaged across respondents from each line of business.

I matched the line of business mean scores to the patents as follows: I used the United States Patent and Trademark Office's (USPTO) concordance between the six-digit U.S. primary patent classification and SIC codes to identify the primary SIC code for each patent. I used the SIC code concordance developed by Levin et al. (1987) to match the patent effectiveness scores to SIC codes. When the SIC code to which the USPTO concordance mapped a patent was at a higher level of aggregation than the SIC code to which the Levin et al. (l987) concordance mapped the patent effectiveness measure, I averaged the Levin et al. (1987) patent effectiveness scores across all lines of business corresponding to that SIC code.

Using the Yale measures to construct the patent effectiveness variable has several important advantages for this study. First, the authors ensured reliability and validity through a pretest with respondents from multiple businesses and through the common identification of major industry innovations (Levin et al. 1987). Moreover, subsequent studies have confirmed the validity and reliability of the measures (e.g., Cohen and Levinthal 1990, Levin et al. 1985, Klevorick et al. 1995).

Second, the Levin et al. (1987) sample was representative of research and development intensive lines of business activity, making the sample appropriate for this study. Moreover, by comparing their results to data on the industries measured by the National Science Foundation, Levin et al. (1987) confirmed the sample's representativeness.

Predictor Variable

Patent Effectiveness. Patent effectiveness was measured as a four-item scale derived from Levin et al. (1987). All items were weighted equally. The first

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[10] I focus on patents licensed to noninventors rather than on patents licensed to inventors because MIT's compensation from inventor-licensees is heavily reliant on equity investments. The returns from equity investments are not directly tied to the performance of specific inventions but to the overall performance of licensees.

[11] Further information is available in Levin et a1. (1987).

item—"patents to prevent competitors from duplicating the process"—was a response to the question, "In this line of business, how effective is each of the following means of capturing and protecting the competitive advantages of new or improved production processes?" The second item—"patents to secure royalty income"—was a response to the same question. The third and fourth items were the same as first and second items, respectively, but were responses to the question, "In this line of business, how effective is each of the following means of capturing and protecting the competitive advantages of new or improved products?" The four items were measured on seven-point scale from 1 (*not at all effective*) to 7 (*very effective*). This scale had a Cronbach's alpha of 0.78.

Control Variables

Year Issued. I control for the year in which the patent was issued because both federal law and MIT policy have changed over time, altering incentives for potential licensees.[12]

Technical Fields. The existence of commercial opportunities and appropriability vary across technical fields (Cohen and Levin 1989), and this variation might influence the decision of MIT inventors to disclose their inventions to the MIT TLO, and the decisions of the TLO to seek patent protection on them. For example, patents are less effective mechanisms for appropriating the returns to invention in semiconductor engineering than in other fields. Consequently, researchers in semiconductor engineering might be more likely to bypass the university patenting and licensing process altogether, except when they have a relationship with potential industry licensees or particularly important inventions. To mitigate this problem, I control for the technology field in which the invention is assigned—chemical, electrical, mechanical, drug (other is the base case). The technology field dummy variables will capture some of the variation in the willingness of inventors to disclose their inventions to MIT and for MIT to seek patent protection.

Funding. Two arguments can be made for the effect of research funding on the licensing of university inventions. The first is that commercial firms generally fund university research in return for a right of first refusal to license any inventions that result from that research. Therefore, industry-funded research should be more likely to be licensed than research funded by the government, foundations, or universities. The second argument is that the Bayh-Dole Act has increased the rate of technology licensing from universities by giving universities the property rights to federally funded inventions. Therefore, in the post-Bayh–Dole era, government funded research should be more likely to be licensed than research funded by foundations or universities. I control for industry and government funding with two dummy variables. The first takes a value of 1 if the research was funded by industry. The second takes the value of 1 if the government funded the research. These variables are nonexclusive since research could receive both government and industry funding.

5. Results

Table 1 provides the descriptive statistics. Table 2 provides a correlation matrix for the variables in the initial regression analysis. Table 3 shows the results of the Cox regression to predict licensing of the 1,397 MIT-assigned patents issued between 1980 and 1996. Table 4 provides a logistic regression to predict whether the licensee of the 717 licensed patents was a noninventor. Table 5 shows results of the Cox regressions to predict termination of the patent license, and Table 6 shows the results of Cox regressions to predict first sale of products or services embodying the licensed patent for the 966 patent licensing efforts between 1980 and 1996. Table 7 shows the results of the Tobit regressions to predict the amount of royalties earned between 1980 and 1997 for the inventions successfully commercialized by noninventors.

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[12] I also examined time as the year of patent application and as a set of dummy variables for each year of patent issue. The results for all of the regression models presented in here are substantively the same when the year of patent application is included instead of year of patent issue. In addition, the use of dummy variables confirmed the increasing probability of license over time in all of the regression models. I report the year issued variable instead of the dummy variables because it provides a more parsimonious summary of the effects of time on the likelihood of license.

Table 1 Descriptive Statistics

Variable	*M*	*SD*	Min.	Max.	*n*
Patent effectiveness	3.93	0.69	1.75	5.32	1,397
Year issued	1989.29	5.00	1979	1996	1,397
Industry	0.14	0.35	0.00	1.00	1,397
Government	0.54	0.50	0.00	1.00	1,397
Electrical	0.38	0.49	0.00	1.00	1,397
Chemical	0.33	0.47	0.00	1.00	1,397
Drugs	0.15	0.35	0.00	1.00	1,397
Mechanical	0.04	0.20	0.00	1.00	1,397
Licensed	0.51	0.50	0.00	1.00	1,397
Terminated	0.34	0.47	0.00	1.00	966
Commercialized	0.21	0.40	0.00	1.00	966
Royalties	50429.68	174875.23	11.49	1,516,717.77	167

As Table 1 shows, 51.3% the MIT-assigned patents were licensed at some time between 1980 and 1996. Of the 717 licensed patents, 537 were licensed to firms not founded by one of the inventors. The 717 licensed patents generated 966 licensing efforts. By the end of 1996, 323 of these licensing efforts had been terminated and 197 had resulted in a first sale. For the 197 patents that resulted in commercialization, 167 were commercialized by at least one firm not founded by the inventors. The distribution of nonequity royalty payments on product sales from the commercialized inventions was fairly skewed. For the 167 patents commercialized by firms not founded by inventors, the average was \$50,429.68, with a range from \$11.49 to \$1,516,717.77.

Table 2 provides the correlations between the independent variables for the full sample. This table demonstrates the importance of controlling for the field of technology in regressions to examine the influence of patent effectiveness. As one might expect, the dummy variable for drug patents was strongly positively correlated ($r = 0.71$), and the dummy variable for electrical patents was strongly negatively correlated ($r = -0.50$), with patent effectiveness.

Table 2 Correlations of the Independent Variables for the Full Sample ($n = 1{,}397$)

	1	2	3	4	5	6	7	8
1. Patent effectiveness	1.00							
2. Industry	−0.01	1.00						
3. Government	0.00	−0.25	1.00					
4. Chemicals	0.05	−0.03	0.02	1.00				
5. Drugs	0.71	−0.00	0.00	−0.29	1.00			
6. Electrical	−0.50	0.02	0.08	−0.55	−0.32	1.00		
7. Mechanical	−0.09	0.06	0.10	−0.15	−0.09	−0.17	1.00	
8. Year issued	−0.12	0.14	0.08	−0.07	−0.07	0.12	−0.03	1.00

Table 3 Cox Regressions to Predict Licensing: 1980–1996

	Model a			Model b		
Variable	*B*	*SE*	Exp(*B*)	*B*	*SE*	Exp(*B*)
Patent effectiveness	0.18	0.08	1.19*	0.45	0.05	1.56****
Year issued	0.07	0.01	1.07****	0.07	0.01	1.07****
Industry	0.42	0.11	1.53****	0.40	0.11	1.49***
Government	0.45	0.08	1.57****	0.41	0.08	1.50****
Chemical	−0.35	0.13	0.70**			
Electrical	−0.51	0.13	0.60****			
Mechanical	−0.52	0.22	0.78			
Drug	0.23	0.17	1.25			
−2 LL	9828.85			9856.03		
χ^2	204.53****			171.18****		

Note. The data set includes 1,397 cases and 717 events.
$^{*}p < 0.05$ (two-tailed). $^{**}p < 0.01$ (two-tailed).
$^{***}p < 0.001$ (two-tailed). $^{****}p < 0.0001$ (two-tailed).
$^{\dagger}p < 0.10$ (two-tailed).

Table 3 predicts the hazard of licensing for the population of 1,397 MIT-assigned patents from 1980–1996. Model 3a provides the base regression. Overall, Model 3a is significant ($\chi^2 = 204.53$, $p < 0.0001$).

Table 4 Logistic Regressions to Predict Noninventor Licensee ($n = 717$)

	Model a			Model b		
Variable	*B*	*SE*	Exp(*B*)	*B*	*SE*	Exp(*B*)
Patent effectiveness	0.66	0.20	1.94****	0.24	0.12	1.27*
Year issued	−0.02	0.02	0.98	−0.02	0.02	0.98
Industry	−0.06	0.26	0.94	0.02	0.25	1.02
Government	0.03	0.20	1.03	0.13	0.19	1.13
Chemical	0.56	0.29	1.76*			
Electrical	0.90	0.30	2.47**			
Mechanical	0.25	0.48	0.60			
Drug	−0.28	0.38	0.75			
−2 LL	770.92			784.36		
χ^2	20.38**			6.93		

$^{*}p < 0.05$ (two-tailed). $^{**}p < 0.01$ (two-tailed).
$^{***}p < 0.001$ (two-tailed). $^{****}p < 0.0001$ (two-tailed).
$^{\dagger}p < 0.10$ (two-tailed).

Table 5 **Cox Regressions to Predict Termination of the License for the Patent: 1980–1996** ($n = 960$)

	Model a			Model b		
Variable	B	SE	Exp(B)	B	SE	Exp(B)
Patent effectiveness	−0.49	0.12	0.61***	−0.32	0.08	0.73****
Inventor-licensee	−2.50	0.74	0.08***	−2.52	0.74	0.08***
Patent × Inventor	0.60	0.17	1.81***	0.60	0.17	1.83***
Year issued	0.06	0.01	1.07****	0.06	0.01	1.07****
Industry	−0.22	0.18	0.80	−0.23	0.18	0.80
Government	0.16	0.13	1.17	0.09	0.13	1.10
Chemical	−0.29	0.18	0.75			
Electrical	−0.38	0.19	0.68*			
Mechanical	−0.19	0.34	0.82			
Drug	0.13	0.25	1.14			
−2 LL	3901.54			3908.11		
χ^2	59.27****			52.29****		

Note. The data set includes 966 cases and 323 events.
*$p < 0.05$ (two-tailed). **$p < 0.01$ (two-tailed).
***$p < 0.001$ (two-tailed). ****$p < 0.0001$ (two-tailed).
†$p < 0.10$ (two-tailed).

As was expected, the likelihood of license was higher for industry-funded (Exp(B) = 1.53, $p < 0.0001$) and government-funded (Exp(B) = 1.57, $p < 0.0001$) patents. The likelihood of license was also higher the newer the patent (Exp(B) = 1.07, $p < 0.0001$). The likelihood of license was lower for chemical patents (Exp(B) = 0.70, $p < 0.01$) and electrical patents (Exp(B) = 0.60, $p < 0.0001$) than for other patents. Consistent with the first hypothesis, the likelihood of license was higher in lines of businesses in which patents were more effective (Exp(B) = 1.19, $p < 0.05$).

Table 6 **Cox Regressions to Predict First Sale: 1980–1996** ($n = 960$)

	Model a			Model b		
Variable	B	SE	Exp(B)	B	SE	Exp(B)
Patent effectiveness	0.43	0.15	1.54**	0.27	0.10	1.31**
Inventor-licensee	3.00	0.85	20.03***	2.90	0.81	18.17***
Patent × Inventor	−0.59	0.20	0.55**	−0.58	0.19	0.56**
Year issued	0.02	0.02	1.02	0.02	0.02	1.02
Industry	0.04	0.22	1.04	0.03	0.22	1.03
Government	0.43	0.18	1.54*	0.50	0.18	1.65**
Chemical	0.55	0.27	1.74*			
Electrical	0.35	0.30	1.42			
Mechanical	−0.27	0.63	0.76			
Drug	−0.09	0.34	0.91			
−2 LL	2409.96			2422.22		
χ^2	41.28****			29.50****		

Note. The data set includes 966 cases and 197 events.
*$p < 0.05$ (two-tailed). **$p < 0.01$ (two-tailed).
***$p < 0.001$ (two-tailed). ****$p < 0.0001$ (two-tailed).
†$p < 0.10$ (two-tailed).

Table 7 **Tobit Regressions to Predict Royalties Earned for Patents Commercialized by Noninventors** ($n = 167$)

	Model a Log (Royalty)		Model b Log (Royalty)	
Variable	B	SE	B	SE
Patent effectiveness	0.44	0.13***	0.17	0.09†
Year issued	−0.06	0.02****	−0.06	0.02****
Industry	0.09	0.20	0.11	0.21
Government	0.05	0.15	0.03	0.17
Chemical	0.13	0.26		
Electrical	0.49	0.28†		
Mechanical	0.24	0.43		
Drug	−0.33	0.31		
Log likelihood	−197.74		−203.39	
χ^2	36.98****		25.68****	

*$p < 0.05$ (two-tailed). **$p < 0.01$ (two-tailed).
***$p < 0.001$ (two-tailed). ****$p < 0.0001$ (two-tailed).
†$p < 0.10$ (two-tailed).

Model 3b provides a robustness check by dropping the dummy variables for technology types. Model 3b shows results consistent with Model 3a. Overall the model is significant ($\chi^2 = 171.18$, $p < 0.0001$). As expected, the likelihood of license was higher for industry-funded (Exp(B) = 1.49, $p < 0.001$) and government-funded (Exp(B) = 1.50, $p < 0.0001$) patents. The likelihood of license was also higher the newer the patent (Exp(B) = 1.07, $p < 0.0001$). Moreover, the likelihood of license was higher in lines of businesses in which patents were more effective (Exp(B) = 1.56, $p < 0.0001$).[13]

One of the potential problems with using the Yale Survey data to measure patent effectiveness is that two lines of business—drugs and electronic computing equipment—might drive the regression results. For this reason, in an unreported Cox regression, I reanalyzed the hazard of licensing for the 1,103 patents that were neither drug patents (SIC 283) nor electronic computing equipment patents (SIC 357).

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[13] I thank Iain Cockburn for pointing out this potential problem and a solution to it.

The results were qualitatively the same as the results reported above. The overall model was significant ($\chi^2 = 117.52$, $p < 0.0001$). Moreover, patent effectiveness increases the hazard of patent license ($\text{Exp}(B) = 1.45$, $p < 0.01$). Thus, the results are robust to the exclusion of two potential outlier lines of business.

Another criticism of the Yale measures is that the effectiveness of patents across lines of business may have changed since the Yale Survey was conducted in 1982. Moreover, the accuracy of the semantic scale items used to measure the effectiveness of patents in the Yale Survey may introduce bias into the analyses. To mitigate these two criticisms, in unreported regressions, I substitute the patent effectiveness measure from the more recent Carnegie Mellon Survey of 1,478 R&D labs in U.S. manufacturing in 1994 for the Yale Survey measure (Cohen et al. 2000). This latter survey measured the effectiveness of patents by asking "respondents to report the percentage of their product and process innovations for which each appropriability mechanism had been effective in protecting the firm's competitive advantage from those innovations during the prior three years. The response categories were: (1) less than 10%; (2) 10% through 40%; (3) 41% through 60%; (4) 61% through 90%; and (5) greater than 90% (Cohen et al. 2000, p. 5)." The responses were averaged across all firms in each line of business.[14]

When I reanalyzed the data, substituting the more recent Carnegie Mellon measures for patent effectiveness for the Yale measures, the results were qualitatively the same as the results that I report above. The overall model was significant ($\chi^2 = 144.02$, $p < 0.0001$). Moreover, the hazard of license was higher in lines of businesses in which patents were more effective ($\text{Exp}(B) = 1.04$, $p < 0.0001$). Therefore, the results do not appear to be an artifact of using the Yale Survey measures.

Table 3 raises the question: How are patents licensed in lines of business in which patents are not effective? Table 4 provides one answer. This table predicts the probability that the 717 licensed patents were licensed to noninventors. Model 4a provides the base regression. Model 4b provides a robustness check by dropping the dummy variables for technology types.

Model 4a[15] is significant ($\chi^2 = 20.38$, $p < 0.01$). The likelihood of license to inventors was higher for chemical ($\text{Exp}(B) = 1.76$, $p < 0.05$) and electrical ($\text{Exp}(B) = 2.47$, $p < 0.01$) patents than for other patents. Consistent with Hypothesis 2, the greater the effectiveness of patents in a line of business, the greater the likelihood of license to a firm not founded by any of the inventors ($\text{Exp}(B) = 1.94$, $p < 0.0001$).

Model 4b supports the analysis in Model 4a. Although the overall model is not significant ($\chi^2 = 6.93$, $p > 0.10$), the greater the effectiveness of patents in a line of business, the greater the likelihood of license to a firm not founded by any of the inventors ($\text{Exp}(B) = 1.27$, $p < 0.05$).

Table 5 provides models to predict the hazard that a patent license is terminated. Model 5a provides the base regression. Model 5b provides a robustness check by dropping the dummy variables for technology types.

Model 5a is significant ($\chi^2 = 59.27$, $p < 0.0001$). This model looks at the interaction of patent effectiveness with inventor-licensee on the hazard of license termination. The hazard of termination was lower for licensed electrical patents ($\text{Exp}(B) = 0.68$, $p < 0.05$) than for other patents. The hazard of termination of licensed patents was also higher, the newer the patent ($\text{Exp}(B) = 1.07$, $p < 0.0001$). Consistent with Hypothesis 3, the hazard of termination of patents licensed to inventor-founded firms was higher in lines of businesses in which patents were more effective ($\text{Exp}(B) = 1.81$, $p < 0.001$).

Model 5b confirms the results of Model 5a. Overall, the model is significant ($\chi^2 = 52.29$, $p < 0.0001$). The hazard of termination of licensed patents was also higher the newer the patent ($\text{Exp}(B) = 1.07$, $p < 0.0001$). Moreover, the hazard of termination of

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[14] I thank Lee Branstetter for pointing out this potential problem and Wes Cohen for suggesting a solution to it.

[15] I also ran Cox regressions to predict the hazard of first license to inventors and to noninventors to ensure that the results were not an artifact of censoring. The Cox regressions confirmed the results of the logistic regressions. The model to predict the hazard of licensing to inventors was significant, and patent effectiveness significantly decreased the hazard of license. The model to predict the hazard of licensing to noninventors was significant and patent effectiveness significantly increased the hazard of license.

patents licensed to inventor-founded firms was higher in lines of businesses in which patents were more effective ($\text{Exp}(B) = 1.83$, $p < 0.001$).

Table 6 provides models to predict the hazard that a product or process embodying the invention reaches first sale, conditional on the licensing of the invention. Model 6a provides the base regression. Model 6b provides a robustness check by dropping the dummy variables for technology types.

Model 6a is significant ($\chi^2 = 41.28$, $p < 0.0001$). This model looks at the main effect of patent effectiveness and the interaction of patent effectiveness with inventor-licensee on the hazard of first sale. The hazard of first sale was higher for licensed chemical patents ($\text{Exp}(B) = 1.74$, $p < 0.05$) than for other patents. In addition, the hazard of first sale was also higher for licensed government-funded patents ($\text{Exp}(B) = 1.54$, $p < 0.05$) than for other patents. Consistent with Hypothesis 4, the hazard of first sale from patents licensed to inventor-founded firms was lower in lines of businesses in which patents were more effective ($\text{Exp}(B) = 0.55$, $p < 0.01$).

Model 6b confirms the results of Model 6a. Overall, the model is significant ($\chi^2 = 29.50$, $p < 0.0001$). The hazard of first sale was also higher for licensed government funded patents ($\text{Exp}(B) = 1.65$, $p < 0.01$) than for other patents. Moreover, the hazard of first sale from patents licensed to inventor-founded firms was lower in lines of businesses in which patents were more effective ($\text{Exp}(B) = 0.56$, $p < 0.01$).

Table 7 predicts the log of royalties received by MIT for the 167 commercialized patents that were licensed to noninventors. Model 7a provides the base regression. Model 7b provides a robustness check by dropping the dummy variables for technology types.

Model 7a is significant ($\chi^2 = 36.98$, $p < 0.0001$). The model shows that conditional on license to noninventors and commercialization, electrical patents earned greater royalties by 1997 than other patents ($B = 0.49$, $p < 0.10$). In addition, conditional on license to noninventors and commercialization, later issued patents generated lower royalties by 1997 than earlier issued patents ($B = -0.06$, $p < 0.0001$). Moreover, consistent with Hypothesis 5, the effectiveness of patents in the line of business increases the amount of royalties earned from commercialized patents licensed to noninventors ($B = 0.44$, $p < 0.001$).

Model 7b confirms the results from Model 7a. Overall, this model is significant ($\chi^2 = 25.68$, $p < 0.0001$). Conditional on license to noninventors and commercialization, later issued patents generated lower royalties by 1997 than earlier issued patents ($B = -0.06$, $p < 0.0001$). Moreover, the effectiveness of patents in the line of business increases the amount of royalties earned from commercialized patents licensed to noninventors ($B = 0.17$, $p < 0.10$).[16]

6. Discussion

This study examined the influence of patent effectiveness on the licensing of, commercialization of, and royalty generation from the population of 1,397 MIT inventions issued between 1980 and 1996. The results show that inventions are more likely to be licensed when patents are an effective mechanism for appropriating the returns to innovation because the patent system reduces the transaction costs of technology transfer. When patents are not an effective mechanism for appropriating the returns to innovation, university technology is likely to be licensed back to inventors because inventor commercialization mitigates the adverse selection, moral hazard, and hold-up problems that plague markets for knowledge.

When patents are effective, licensing to noninventors reduces the likelihood of license termination and increases the likelihood of invention commercialization by allowing commercialization to be undertaken by economic actors who possess a comparative

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[16] Because I cannot conduct an experiment to test whether exogenous variation in the level of patent effectiveness influences the mode and success of commercialization, I assume that patent effectiveness is not correlated with the unobserved "quality" of the inventions in my analyses. I also attempt to control for invention "quality." In unreported regressions, I analyze the same regression models described above, controlling for the count of forward citations to the MIT inventions. The influence of the patent effectiveness variable is qualitatively the same in the alternative regressions that control for citations, suggesting that the effects are robust to efforts to control for invention quality. I do not report these alternative regressions both because of space limitations and because forward citations are an imperfect measure of patent quality. Not only is the correlation between the financial return from innovation and citation counts relatively low, forward patent citations may themselves be influenced by the outcome of attempts to license the inventions.

advantage in that activity. As a result, the effectiveness of patents in a line of business increases the royalties earned from inventions licensed to noninventors.

Limitations

This study is not without limitations. First, the study used semantic scales that lack an objective anchor to measure the effectiveness of patents (Levin et al. 1987). Consequently, the respondents may have varied significantly in their perceptions of the types of competitive advantages that are effective in their industries. However, these biases are likely to be limited by the approach used to analyze the data. Levin et al. (1987) averaged the semantic responses across respondents in each line of business, and this averaging should have dampened individual-level variation in perceptions. Moreover, there is no a priori theoretical reason to believe that the perceptual biases of the respondents differ systematically across industries. Furthermore, I obtain qualitatively similar results using the more recent Carnegie Mellon survey measures for patent effectiveness, which do not employ a semantic scale without an objective anchor.

Second, U.S. patent classes do not map perfectly on industry classifications, such as SIC codes. To match patent classes to industries, I relied on the USPTO patent–SIC concordance. Because this concordance is imperfect, this mapping procedure introduces noise into the data, which makes the regression estimates imprecise. Moreover, other concordances that make different patent class to SIC matches also exist. The differences between the matches made by the USPTO and other concordances may also introduce noise into the analyses. Nevertheless, I use the USPTO concordance because no more precise mechanism currently exist for matching patents to SIC codes.

Third, the study analyzed data from a single research university, and technology licensing may differ significantly across universities. Given its disproportionate influence on the generation of new technology, MIT may be a special case that might limit the generalizability of the findings shown here. Future research should explore this issue.

Fourth, this study does not capture several dimensions of university inventions that may influence technology licensing. Jensen and Thursby (forthcoming) have shown that university technology is more likely to be licensed if it is at a later stage of development, a dimension not measured here. Moreover, the study does not examine the effect of social relationships between licensing officers, inventors, and industry representatives, even though Shane and Cable (1998) found that these relationships were important, particularly when start-ups or small companies licensed the technology.

Fifth, the results shown in this article are not unconditional estimates of the hazard of licensing, but are estimates conditional on MIT's decision to file for a patent.[17] Only 60% of university invention disclosures result in patent applications. If patent effectiveness is important in obtaining a license (as the analysis here shows), then the TLO should be more likely to file a patent in those lines of business in which patents are more effective. Therefore, the results presented here are conditional on MIT's prior selection of which invention disclosures to patent. Nevertheless, the tests presented here are conservative because they are biased against finding an effect for the patent effectiveness variable. If the TLO considers patent effectiveness in the line of business in deciding which invention disclosures to patent, then the magnitude of the effect of the patent effectiveness variable on licensing is understated.

Sixth, the analyses presented here are not independent of each other. If one knew with reasonable accuracy the behavior, probability distributions over future contingencies, and expectations of decision makers in the licensing process, a dynamic structural model would be the best approach to analyzing these data. I do not follow this approach here because the behavioral processes underlying university technology licensing are not well enough understood to specify such a model in a reasonable way. Readers are therefore cautioned to exercise caution in interpreting the coefficients. The results do not allow us

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[17] I was unable to obtain data from MIT's invention reports. Such data would determine if the probability of patent application was influenced by the effectiveness of patents in a line of business.

to make counterfactual statements about alternative policy regimes.

7. Implications for Research Policy

Despite the limitations described above, the results have important implications for two related areas of research: innovation strategy and management and technology entrepreneurship. In the subsections below, I discuss the implications of the results for each of these areas.

Innovation Strategy and Management

The results of this study have useful implications for the field of innovation strategy and management. Many observers have noted that innovation increasingly is taking place through contractual arrangements. However, transaction cost economics explains that contractual arrangements are not always the best way to manage innovation (Pisano and Mang 1993). This study provides some empirical evidence about this process, albeit in the specialized case of university inventions. The data show that when patents are effective, licensing by noninventors is more likely to result in commercialization than is licensing back to inventors. As a result, this study provides empirical evidence in answer to the question: When should innovation be internalized and when should it be contracted out?

In addition, the results provide insight into Schumpeterian dynamics in high technology industries. Many researchers have argued that when the locus of innovation lies outside of incumbent firms, the development of new technology spurs a process of creative destruction through which innovators replace incumbent firms (Christiansen and Bower 1994, Foster 1986). However, in many high technology industries, like biotechnology, this external locus of innovation does not result in creative destruction (Gans and Stern 2000).[18]

Gans and Stern (2000) have argued that one reason for the between industry variation in the tendency of incumbents to withstand external innovation lies in the effectiveness of markets for knowledge. Where markets for knowledge are effective, nonincumbent innovators can license their technologies to established firms. This process allows external innovators to earn returns to innovation without competing with incumbents in product markets. This study provides support for the core assumption of Gans and Stern's (2000) argument. When patents are ineffective, (university) inventors are more likely to found firms to commercialize their inventions. In contrast, when patents are effective, (university) inventors are more likely to license their inventions to noninventors.

Finally, the results of this study are consistent with Anand and Khanna's (2000) argument that technology licensing can be explained largely on the basis of industry differences in patent strength. Their explanation has the advantage of parsimony over many alternative explanations for licensing because it does not require assumptions about the importance of the technology being transferred, demand conditions, or market structure.

Technology Entrepreneurship

The results of this study also have useful implications for the field of entrepreneurship. The results provide evidence that university inventors become entrepreneurs because of failures in the market for knowledge, suggesting that inventor-entrepreneurship is a second-best solution to the commercialization of new technology. This view stands in contrast to the perspective of most of the entrepreneurship literature (and the popular press), which argues that independent entrepreneurship is a better mechanism for university technology commercialization than commercialization by established firms. This difference is important because theories in which independent entrepreneurship is considered the best approach to technology commercialization yield different implications from theories in which independent entrepreneurship is considered a second-best approach.

Moreover, the results of this study support a small literature that argues that who becomes an entrepreneur depends more on information and opportunities than on the psychological attributes

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[18] For example, most new biotechnology products have been based on discoveries made by entities other than research and development units of major pharmaceutical firms (Gans et al. 2000).

of entrepreneurs and nonentrepreneurs (Shane and Venkataraman 2000, Shane 2000). Traditionally, entrepreneurship research has argued that firm formation occurs because certain people possess special attributes (e.g., tolerance of uncertainty, need for achievement, locus of control) that make them better able than others to undertake the entrepreneurial process (Khilstrom and Laffont 1979, McClelland 1961). In contrast to the personological perspective on entrepreneurship, this study shows that the nature of technological opportunities themselves influence whether opportunities will be sold to others or exploited by inventor-entrepreneurs.

Conclusion

This paper draws on transaction cost economics to show that (1) university inventions are more likely to be licensed when patents are effective; (2) when patents are not effective, university technology tends to be licensed back to inventors; (3) when patents are effective, licensing to noninventors reduces the likelihood of license termination and increases the likelihood of invention commercialization; and (4) the effectiveness of patents increases royalties earned for inventions licensed to noninventors. Hopefully, this study will spur future researchers to consider the influence of appropriability on university technology licensing.

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