Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing

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This paper analyzes the relationship between technology licensing and the effectiveness of patent protection. Using the 1994 Carnegie Mellon survey on industrial research and development (R&D) in the United States, we develop and test a simple structural model in which the patenting and licensing decisions are jointly determined. We find that increases in the effectiveness of patent protection increases licensing propensity, but only when the firm lacks specialized complementary assets required to commercialize new technologies. In contrast, for firms with specialized complementary assets, increases in patent effectiveness increase patenting propensity but reduce the propensity to license. We present systematic cross-industry empirical support for the proposition that intellectual property protection is a key determinant of the vertical boundaries of the firm and the market for technology but that its impact is mediated by a firm's ownership of specialized complementary assets.

1. Introduction

Over the last two decades, technology-related alliances, such as contract research and development (R&D), R&D joint ventures, and especially technology licensing, have grown rapidly. Estimates for the 1980s suggest that such alliances account for as much as 10%–15% of total civilian R&D in the Organization for Economic Cooperation and Development (OECD) countries (Arora et al. 2001, p. 43). Both start-up and established firms in industries such as biotechnology and pharmaceuticals, semiconductors, instruments, and chemicals have relied extensively on licensing to appropriate rents from their innovations. In pharmaceuticals, 38% of the new chemical entities approved by the U.S. Food and Drug Administration from 1963 to 1999 were licensed (DiMasi 2000). Market-based licensing of chemical processes by established firms such as Union Carbide, BP, Shell, and even Dow and DuPont is also well documented (Arora and Fosfuri 2003, Fosfuri 2004a).[1]

Similarly, over the last two decades, patenting in the United States has grown rapidly, due in part to the increasing importance of patent-intensive sectors such as pharmaceuticals. However, part of the increase in growth is due to increases in patent propensity in sectors such as semiconductors and electronics (Kim and Marschke 2004), in which patents have not traditionally been seen as very important, partly reflecting the rise of firms specializing in chip design (Hall and Ziedonis 2001). Changes in the legal environment have been important as well. In 1982, the Court of Appeals for the Federal Circuit was established to make patent law more uniform; indirectly, it also strengthened it. Patents have also become a growing preoccupation of management (Grindley and Teece 1997, Rivette and Kline 1999).

It is plausible that these trends are related. In particular, the link between patenting and licensing can be analyzed in light of the challenges faced by sellers and buyers of technology, highlighted by Arrow (1962) and fleshed out in greater detail by Mowery (1983), Williamson (1991), and others. Arrow (1962) pointed out that a potential licensee would naturally wish to verify the quality of the invention before paying for it. However, once the inventor discloses the invention, the potential licensee would have little incentive to pay for it. Patents are a possible solution because the invention can be disclosed without fear of imitation. Licensing is possible, in principle, even without patents. Anton and Yao (1994) provide a theoretical

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[1] Patent-based technology transactions are, of course, not new. Lamoreaux and Sokoloff (1998) document the extensive trade in patent rights in the United States in the late 19th century. Also, data availability limits the focus of this paper to technology licensing, but the market for technology has other dimensions as well, including strategic alliances and mergers and acquisition.

model of how an invention protected only through secrecy can be licensed by threatening a licensee who reneges with enhanced competition through further disclosure. Arora (1996) provides a model and supporting empirical evidence wherein tacit know-how can be bundled with other inputs (which could include patents) in a self-enforcing contract. However, although plausible, the empirical importance of these alternative mechanisms remains unknown. Thus, Teece (1986) has argued that licensing is mainly recommended if the innovator enjoys strong patent protection *and* lacks complementary assets such as manufacturing and marketing. Implicit in Teece's prescription is the notion that access to complementary assets is difficult—typically they cannot be "rented," and acquiring them is costly and time consuming.

The available evidence (reviewed in §2) of the impact of patents, or their effectiveness, on licensing is limited, typically confined to studies of individual industries, and the empirical findings are inconclusive. This paper shows that one key reason for the mixed evidence, which has been overlooked by previous studies, is that the impact of patent protection on licensing is mediated by specialized complementary assets required for commercializing innovations: Effective patents are more likely to encourage licensing among firms that lack such assets compared with firms that possess them. Patent protection can affect licensing through two routes: the patenting decision (because nonpatented inventions are difficult to license) and the licensing decision conditional on patenting. By estimating a system of simultaneous equations, where the patenting and licensing decisions are jointly determined, we are able to identify the differential impact of patent effectiveness on both the probability of licensing and licensing conditional on patenting and to disentangle the mediating role of specialized complementary assets. We use data from the 1994 Carnegie Mellon survey on U.S. industrial R&D (Cohen et al. 2000).

This paper also contributes to the literature on the role of patents in appropriating rents from innovation. Surveys by Mansfield (1986), Levin et al. (1987), and Cohen et al. (2000) suggest that patents are featured as an effective appropriability strategy in only a few industries. Arora et al. (2003) estimate that only for a small fraction of innovations do patents provide greater net expected returns. We contribute to this literature by analyzing how the payoffs to patenting and licensing are conditioned by specialized complementary assets. Our results imply that although the strength of patent protection increases the returns to patenting, the source of the increase is more likely to be licensing for firms lacking specialized complementary assets. Our results also imply

that the presence of specialized complementary assets enhances the value of patent protection.

However, our paper does not address the long-run configuration of firms and industries. In particular, it cannot address fully when industries can feature a division of innovative labor (Arora et al. 2001). For this, we would have to examine how and when innovating firms strategically choose to acquire (or not) various complementary assets. The resource-based theory of the firm (e.g., Wernerfelt 1984, Dierickx and Cool 1989, Barney 1991, Amit and Schoemaker 1993) suggests that firms are distinguished by capabilities that are valuable, rare, and difficult to imitate. In the same spirit, we assume that firms are endowed with different levels of specialized complementary assets, at least in the short term.

In §2, we present a simple model of patenting and licensing decisions, the hypotheses to be tested, and the empirical specification. Section 3 describes the data and measures used for estimation, and §4 discusses the results. Section 5 examines the robustness of the results to alternative assumptions about specifications and endogeneity. The conclusion follows in §6.

2. Theory Development and Empirical Specification

In this section, we first present a simple empirical model to better structure the development of our hypothesis. In particular, we posit that a firm that has developed an innovation faces four mutually exclusive and exhaustive options: (1) patent and license; (2) patent and not license; (3) not patent and license; and (4) not patent and not license. The probabilities that any given innovation is patented or licensed are as follows:

$$\Pr(\text{Patent}) = \Pr(\text{Patent and License})$$
$$+ \Pr(\text{Patent and Not License}), \quad (1\text{-}1)$$

$$\Pr(\text{License}) = \Pr(\text{Patent and License})$$
$$+ \Pr(\text{Not Patent and License}). \quad (1\text{-}2)$$

In our data, firms that do not patent rarely license. In particular, cross-tabulating our data by licensing and patenting propensities shows that less than 10% of licensors do not patent, but nearly 33% of nonlicensors do not patent; and that only 12% of nonpatentees license, whereas about 40% of the patentees license. Therefore, our data strongly suggest that the presence of a patent is almost essential for licensing, and it will be difficult to empirically estimate the determinants of license and not patent. Accordingly, we set Pr(License and Not Patent) equal to 0 in (1-2) and drop the 25 anomalous observations from the analysis.[2]

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[2] Section 5.4 discusses the robustness of this assumption, including a more detailed examination of those cases where licensing is apparently not based on a patent.

Let V_L denote the payoff to a firm if it patents and licenses a given innovation, and V_P if it patents but does not license it. Similarly, let V_S denote the payoff if the firm keeps the innovation secret (not patent) and also does not license it. Assuming that firms choose the action with the highest payoff, we obtain

$$\Pr(\text{Patent}) = \Pr(V_L = \text{Max}\{V_L, V_P, V_S\})$$
$$+ \Pr(V_P = \text{Max}\{V_L, V_P, V_S\}), \quad (2\text{-}1)$$

$$\Pr(\text{License}) = \Pr(V_L = \text{Max}\{V_L, V_P, V_S\}). \quad (2\text{-}2)$$

We use a linear random utility specification, obtained by incorporating an additive stochastic component to each payoff, and assume that the stochastic terms are independent and identically distributed (i.i.d.) across innovations with Type 1 extreme value (Gumbel) distribution and are observed by the firm but not the econometrician. The licensing and patenting probabilities[3] are (cf. McFadden 1973)

$$\Pr(\text{Patent}) = [\exp(V_L) + \exp(V_P)] \big/$$
$$[\exp(V_L) + \exp(V_P) + \exp(V_S)], \quad (3\text{-}1)$$

$$\Pr(\text{License}) = [\exp(V_L)] \big/$$
$$[\exp(V_L) + \exp(V_P) + \exp(V_S)], \quad (3\text{-}2)$$

$$\Pr(\text{License} \mid \text{Patent}) = [\exp(V_L)] \big/$$
$$[\exp(V_L) + \exp(V_P)]. \quad (3\text{-}3)$$

Our data are at the firm level, and we do not observe whether a specific innovation is licensed or patented. Rather, we observe the proportions of innovations a firm patents or licenses. Thus, although our setup is similar to a multinomial logit, our dependent variables are not binary variables but proportions. We treat the probability of an event as the true mean of the observed proportion. It is also obvious that we cannot identify the individual payoffs, only the differences. By dividing both the numerator and denominator of the probabilities by $\exp(V_S)$, we get the estimating equations

$$Y_1 = [\exp(V_L - V_S) + \exp(V_P - V_S)] \big/$$
$$[\exp(V_L - V_S) + \exp(V_P - V_S) + 1] + \nu_1, \quad (4\text{-}1)$$

$$Y_2 = [\exp(V_L - V_S)] \big/$$
$$[\exp(V_L - V_S) + \exp(V_P - V_S) + 1] + \nu_2. \quad (4\text{-}2)$$

Here, Y_1 and Y_2 are the patenting and licensing propensities, $V_L - V_S$ and $V_P - V_S$ are made functions of

observed firm and industry characteristics discussed below, and the econometric error terms, ν_1 and ν_2, represent sampling errors that account for the difference between theoretical and empirical probabilities.[4]

2.1. Determinants of $V_L - V_S$, $V_P - V_S$ and Implications for Patenting and Licensing Propensity

Our empirical specification makes it clear that observed behavior—the decision to patent or license—does not depend on the underlying payoffs in a straightforward manner. For instance, a variable that increases the licensing payoff, V_L, could nonetheless decrease licensing propensity if it increases V_P sufficiently. Accordingly, we develop our hypotheses in two parallel tracks. We first discuss the impacts of patent effectiveness on relative payoffs. We then develop the implications for patent and licensing propensities. The theoretical predictions are summarized in Tables 1a and 1b. The appendix formalizes the hypothesis developed and provides proofs.

2.1.1. Patent Effectiveness. We use the term "patent effectiveness" to mean strength of patent protection. A variety of factors may drive the effectiveness of patents, including increases in length or breadth of protection, greater codifiability of knowledge, decreases in costs of application, and costs of disclosure (Horstmann et al. 1985). Because we cannot empirically distinguish among these, we use effectiveness as a summary measure. An increase in patent effectiveness should increase $V_L - V_S$ as well as $V_P - V_S$, thus unambiguously increasing patent propensity. However, although patents are virtually always required for licensing, an increase in patent effectiveness has conflicting effects on the decision to license: While more effective patents increase V_L, they also increase V_P, so that the impact on licensing propensity is ambiguous. More effective patent protection increases the net benefits from licensing (e.g., by decreasing transaction costs or by increasing the licensor's bargaining power) but may also increase the opportunity cost of licensing by enhancing the payoff from the exclusive commercialization of the innovation.

Indeed, the available empirical evidence is mixed. Using a sample of Massachusetts Institute of Technology inventions, Gans et al. (2002) find that the presence of patents increases the likelihood that an inventor will license to an incumbent rather than

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[3] Note that (3-3) can be derived from (3-1) and (3-2). Estimation of (3-3) by itself is feasible but inefficient, because it would require that we drop about 25% of the sample with zero patent propensity (see §5.3).

[4] Our framework assumes that the licensing and the patenting decisions are made at the same time. Firms may patent first and later decide whether to license. Estimates of a sequential model yield similar results (see §5.3), but, with cross-sectional data, identification in the sequential model relies more heavily upon functional form assumptions.

Table 1a   The Predicted Effect of Patent Protection and Complementary Assets on Licensing and Patenting Payoffs

	$V_L - V_S$ Licensing payoffs relative to not patenting	$V_L - V_P$ Licensing payoffs relative to patenting and not licensing	$V_P - V_S$ Patenting and not licensing payoffs relative to not patenting
Patent effectiveness (Hypothesis 1a)	+	?	+
Complementary assets × patent effectiveness (Hypothesis 2a)	Null	−	+

Table 1b   The Predicted Effect of Patent Protection and Complementary Assets on Licensing and Patenting Propensities

	Probability of patenting	Probability of licensing conditional on patenting	Probability of licensing
Patent effectiveness (Hypothesis 1b)	+	?	?
Complementary assets × patent effectiveness (Hypothesis 2b)	?	−	−

enter the product market by commercializing the invention. Anand and Khanna (2000) find that in the chemicals sector, where patents are believed to be effective, there are more technology deals—a large fraction of these are arm's length and involve exclusive licenses, a large fraction concerns future technologies rather than existing technologies, and a small fraction is among related firms than for all sectors as a whole. In contrast, Cassiman and Veugelers (2002) do not find that more effective patents encourage Belgian firms to enter into collaborative R&D arrangements.

Evidence from cross-national data is also mixed. Some studies find a positive association between patents and licensing. Yang and Maskus (2005) report a strong positive relationship between improved intellectual property rights (IPR) regimes and licensing by U.S. multinational corporations. Analyzing data on international technology licensing contracts of Japanese firms, Nagaoka (2002) finds that weak patent regimes are associated with an increase in the fraction of transfers to an affiliate (such as a subsidiary), rather than to an unaffiliated firm. Smith (2001) finds that U.S. firms are more likely to export or directly manufacture than to license technology in countries with weak patent regimes. A study using French data on the export of technology services finds that such exports are greater for countries with more effective patent protection, but mainly for higher-income countries (Bascavusoglu and Zuniga 2002).

Other studies cast doubts on the link between patent protection and the extent or form of international technology licensing. Fink (2005) finds a very weak relationship using German data. Puttitanun (2003) reports a higher response of direct investment than licensing to changes in the level of IPR protection. Similarly, Fosfuri (2004b) does not find that patent protection significantly affects the extent or composition of technology flow (as joint venture, direct investment, or licensing) in the chemical sector. The mixed nature of the findings is further reflected in a recent study by Branstetter et al. (2006). Using detailed data on the technology royalty payments received by U.S. firms and controlling for country, industry, and firm fixed effects, they find that stronger patent protection does not increase the transfer of technology by U.S. multinationals to unaffiliated parties. However, it *does* increase the flow of technology to affiliates. The above discussion leads us to the following hypotheses:

HYPOTHESIS 1A. *Increases in patent effectiveness increase $V_L - V_S$ and $V_P - V_S$. The impact on $V_L - V_P$ is ambiguous.*

HYPOTHESIS 1B. *Increases in patent effectiveness increase patent propensity. Increases in patent effectiveness may increase or decrease the share of licensing in patented innovations.*

2.1.2. Complementary Assets and Their Conditioning Role. Successful innovation requires manufacturing, marketing, and a variety of other complementary assets (cf. Teece 1986). If these assets were "generic" and hence could be readily accessed through the market, they could be valuable, but their strategic importance would be limited (e.g., Barney 1991, Rothaermel and Hill 2005). However, manufacturing and marketing assets required for commercializing an innovation are often not generic. Instead, they are specialized to the innovation and thus have limited alternative uses. Their market availability is also limited because firms tend to gain control over them to avoid potential bargaining problems. They are difficult to imitate because they result from the interaction of people from different parts of a firm's organization and are built over long periods of time (Teece 1992). Indeed, Shane (2001) finds that specialized complementary assets increase the likelihood that technology will be exploited inside a firm. Conversely, Gans et al. (2002) find that technology start-ups (which lack complementary assets) are more likely to ally with incumbents in sectors where complementary assets are costly to acquire. In our setup (nongeneric) complementary assets should increase V_P and V_S and, as we argue below, should have little impact on V_L.

Our focus in this paper is not on this direct impact of complementary assets. Rather, we want to highlight an important interaction between a firm's complementary assets and patent effectiveness. In particular, if higher patent effectiveness implies that rivals are unable to produce close substitutes, then more effective patent protection should translate into a "larger market" for the patented innovation. An innovator with specialized complementary assets should be able to profit more from a larger market than an innovator lacking such assets. For instance, if complementary assets imply that the innovative product can be produced at a lower cost or that quality can be increased at a lower cost, then this is more profitable, the greater the volume of demand for the product. Thus, V_P should increase faster with patent effectiveness for firms with specialized complementary assets.

For the other payoffs, this interaction effect is absent. The payoff from not patenting, V_S, cannot, by definition, vary with patent effectiveness. Similarly, the payoff from licensing, V_L, should depend on the complementary assets of the *licensee* rather than those of the licensor. It follows that $V_L - V_P$ should fall faster with patent effectiveness for firms with specialized complementary assets. Similarly, the positive impact of patent effectiveness on $V_P - V_S$ is larger for firms with the specialized complementary assets, but the impact on $V_L - V_S$ is unaffected.

Insofar as the ownership of specialized complementary assets also increases licensee bargaining power in licensing negotiations (e.g., Gans et al. 2002), the impact of complementary assets on V_L is positive (rather than zero) so that the impact of the interaction between patent effectiveness and complementary assets on $V_L - V_P$ is ambiguous. The empirical model does allow for a specialized complementary asset to affect V_L, but the empirical estimates show that the estimate of such impact, if any, is small.[5]

The consideration of the interaction effect on relative payoffs is also critical to evaluate the impact of patent effectiveness on licensing probabilities. If the positive interaction effect on V_P is sufficiently strong, both the propensity to license and the share of licensing in patented innovations will increase faster (or decrease more slowly) with patent effectiveness for firms lacking the relevant specialized complementary

assets. To summarize, we will test the following hypotheses:

HYPOTHESIS 2A. *The impact of increasing patent effectiveness on $V_L - V_S$ is the same for firms with different levels of specialized complementary assets. However, the impact of increasing patent effectiveness on $V_P - V_S$ is higher for firms owning specialized complementary assets.*

HYPOTHESIS 2B. *The impact of patent effectiveness on both licensing and the share of licensing in patented innovations is weaker for firms with specialized complementary assets.*

3. Data and Variables

The data used come from the Carnegie Mellon survey (CMS) on industrial R&D (Cohen et al. 2000). The population sampled is that of all R&D labs located in the United States conducting R&D in manufacturing industries as a part of a manufacturing firm. The sample was randomly drawn from the eligible labs listed in the *Directory of American Research and Technology* (Bowker 1995) or belonging to firms listed in Standard and Poor's Compustat, stratified by three-digit SIC industry. R&D lab managers were asked to answer questions with reference to the "focus industry"—defined as the principal industry for which the unit was conducting its R&D. Valid responses were received from 1,478 R&D units, with a response rate of 54%. The data refer to the period 1991–1993. After trimming for outliers and dropping observations with missing data for the variables of interest, we obtain a final sample of 757 observations.[6] Table 2 provides descriptive statistics for the variables used in the analysis. Also, although we use the term "firm" for the unit of analysis, the unit of analysis is the business unit within the parent firm, operating in the "focus industry" of the responding R&D lab.

3.1. Endogenous Variables

Licensing Propensity. The CMS asks respondents to state the percentage of their R&D projects over the last three years that were undertaken with the objective of earning licensing revenues. (Projects could have multiple objectives.) There were five response categories: <10%, 10%–40%, 41%–60%, 61%–90%, and >90%. We used the midpoints of each response category. For the first category, it is likely that most respondents actually meant zero. Thus, we assigned all respondents in the first category zero licensing

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[5] Additional support for this assumption comes from the empirical estimates of the direct impact of complementary assets on licensing propensity. If the bargaining power effect were negligible, the direct impact ought to be negative. Our results indicate that the impact of complementary assets on both licensing and the share of patented innovations that are licensed is indeed negative. The structural estimates indicate that complementary assets decrease $V_L - V_P$ as well as $V_L - V_S$. In sum, the results are consistent with a small or negligible impact of complementary assets on V_L.

[6] This also reflects the exclusion of business units with more than 10 employees, R&D units reporting more than 50 patent applications per million dollars of R&D, and those reporting an R&D budget of less than or equal to $100,000. Including very small units does not affect our results but is consistent with Arora et al. (2003) and Cohen et al. (2000).

Table 2 Descriptive Statistics

	Mean	Median	St. dev.	Min	Max
Endogenous variables					
Licensing propensity	0.06	0	0.15	0	0.95
Patent propensity	0.29	0.25	0.27	0	1
Explanatory variables					
Business unit employees (Log)	6.60	6.45	2.08	2.30	13.01
Patent effectiveness	0.35	0.25	0.29	0.05	0.95
Complementary assets	0.50	0	0.50	0	1
% basic research	0.03	0	0.06	0	0.50
Importance of basic science	1.93	2	0.96	0	3
Importance of medical science	0.66	0	1.00	0	3
Number of technological competitors	3.95	4	4.75	0	32
Parent firm is global	0.78	1	0.42	0	1
Parent firm is foreign	0.10	0	0.30	0	1
Parent firm is public	0.66	1	0.47	0	1

$N = 757$

propensity, unless they indicated that the possibility of earning licensing revenue was one of the reasons for patenting.[7] The available measure of licensing is not based on actual licensing deals but on firms' willingness to invest in R&D with the intention to license. Our ex ante measure thus excludes cross-licensing deals and transactions that take place in the shadow of infringement suits (Hall and Ziedonis 2001). Because we lack information on technology buyers, our measure of licensing propensity may be better than the actual number of licensing deals. Note that licensing propensity is not separately available for products and processes.

Patent Propensity. The CMS asks respondents for the percentage of product and process innovations for which they applied for patents in the period 1991–1993 in the United States. We computed a weighted average of product and process patent propensities using the percentage of R&D effort devoted to product and process innovations, respectively, as weights, as reported by the CMS respondents.

3.2. Explanatory Variables

Patent Effectiveness. The CMS asks respondents to indicate the percentage of their product and process innovations for which patent protection had been effective in protecting their firm's competitive advantage from those innovations during the

prior three years. There were five mutually exclusive response categories for product and process innovations separately: <10%, 10%–40%, 41%–60%, 61%–90%, and >90%. We computed a weighted average of the product and process scores (using midpoints), with the percentage of R&D effort devoted to product and process innovations as weights, to construct *patent effectiveness*.

To inform our interpretation of this measure, we analyzed the relationship between reasons to patent and not to patent and the respondents' patent effectiveness scores, using an ordered probit model (Arora et al. 2003). The results indicate that patent effectiveness is indeed a broad summary measure of the various costs (such as information disclosure) and benefits of patenting (including preventing imitation, facilitating technology negotiations, or building patent fences). In §5, we report results where we instrument for patent effectiveness to address the possibility that firms that patent a lot also perceive patents to be effective, or that there are unmeasured differences in knowledge that drive both patenting and patent effectiveness.[8]

Complementary Assets. We focus on specialized manufacturing capability. The CMS provides a measure for the frequency of face-to-face interaction between personnel from R&D and production, measured in a four-point Likert scale.[9] We constructed a binary variable, *complementary asset*, which takes value 1 if R&D and manufacturing personnel interact daily (the median value is weekly interaction).

In general, measuring the degree of specialization is difficult but, as Teece (1992) suggests, complementary assets often arise from the interaction and learning over time of people from different parts of a firm's organization. This is especially relevant for the interaction with R&D, which typically requires organizationally embedded interpersonal and interfunctional activities (Zhao et al. 2005). Previous studies have used measures of manufacturing or sales force (e.g., Tripsas 1997, Nerkar and Roberts 2004) or financial assets as measures of complementary capabilities (e.g., Helfat 1997). Our measure does not simply reflect a firm's ownership of complementary manufacturing capabilities, because all firms in our sample have manufacturing capability. Further, we control

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[7] This procedure increases the sample probability of licensing conditional on patenting, because only patentees can indicate whether licensing was a motive for patenting. However, using the midpoint of the first category gives similar results.

[8] Our patent effectiveness measure does not take into account the skewed nature of the net returns from patenting (Schankerman and Pakes 1986, Scherer and Harhoff 2000). This is relevant only insofar as one suspects that even as the percentage of innovations for which patents are effective increases, the average return to patenting falls.

[9] Respondents were asked, "How frequently do your R&D personnel talk face to face with personnel from the Production, Marketing or Sales, and Other R&D units functions?"

for size, which also proxies for the manufacturing and marketing assets. Indeed, the extent of interaction between the R&D and manufacturing functions measures how *important* it is for the innovating firm to also have manufacturing capability—the quintessence of the notion of specialized complementary assets.[10]

There are other possible—and broader—measures of specialized complementary assets, such as the importance of complementary manufacturing and marketing assets in appropriating the profits from innovations (cf. Cohen et al. 2000, Shane 2001, Gans et al. 2002). In the online appendix (http://mansci. pubs.informs.org/ecompanion.html) we show that their use in the empirical model yields qualitatively similar—albeit less precise—results than those presented here. Finally, it is plausible that firms that intend to license may choose more modular organizations, with fewer interactions between R&D and manufacturing. We probe the robustness of our results to such endogeneity in §5.

Business Unit Size. We controlled for size using business unit size, measured by the log of the number of business unit employees. We also experimented with firm size, measured by the log of the total employees of the unit's parent firm, as well as both measures of size, and obtained similar results.

Nature of Knowledge. Tacit technology is costly to transfer, implying lower licensing payoffs (Teece 1977). Typically, technologies that are strongly science based, especially in sectors such as chemicals, molecular biology and genetics, and in some cases, semiconductors, are less likely to be tacit, and patents are more likely to be effective (Arora and Gambardella 1994, Winter 1987, Anand and Khanna 2000). The CMS provides various measures of the degree to which the firm's knowledge is science based and thus likely to be codifiable or nontacit.[11] We use three such variables. One measure, labeled *importance of basic science*, represents the maximum score computed across all the fields, except the engineering fields and the medical and health science field. A second measure, labeled *importance of medical science*, represents the importance of the medical and health science field

alone. A third measure is the *percentage of R&D effort devoted to basic research*, defined as scientific research with no specific commercial objective.

Basic research is arguably more codifiable than applied research. For example, basic biotech research has highly codifiable output, and there is ample evidence of contract R&D and technology licensing. On the other hand, advances in internal combustion engines are still based on a great deal of trial-and-error type research, the results are difficult to codify effectively, and there is relatively little contract R&D or technology licensing. Even in biopharmaceuticals, fermentation and other production technologies tend to be tacit. The share of basic research (and perhaps the importance of basic science) has an alternative, although not mutually exclusive, interpretation as well. As Nelson (1959) points out, basic scientific research is more likely to result in useful knowledge that a firm is itself unable or unwilling to commercialize or the use of which may be much broader than the firm's domain of operation. In such cases, licensing is a natural means of appropriating the benefits of such research.[12]

Technological Competition. Technological rivalry is likely to raise the payoff to patenting and may also raise the opportunity cost of licensing, particularly if there is a prospect of valuable knowledge leaking out (e.g., Hill 1992, Ceccagnoli 2005). We used the midpoint of the *number of technological rivals*, which in the CMS is reported as a categorical variable in the following ranges: 0, 1–2, 3–5, 6–10, 11–20, or >20.[13]

Industry Fixed Effects. We included seven industry dummy variables to control for industry effects, such as licensing and patenting norms.[14]

Other Controls. We used binary variables indicating whether the firm owning the R&D lab was *global* (also sells products in Japan or Europe), *foreign* (the parent is located abroad), or *public* (publicly traded).

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[10] Of course, some industry-specific studies have the advantage of being able to use finer measures of specialized complementary assets: Tripsas (1997) uses font libraries in her study of the typesetting industry; Thomke and Kuemmerle (2002) use therapeutical area-specific chemical libraries in pharmaceuticals, and Penner-Hahn and Shaver (2005) use the stock of fermentation patents as a measure of complementary manufacturing capabilities for Japanese pharmaceutical firms.

[11] Respondents were asked to rate (on a four-point Likert scale) the importance of different fields of science and engineering in terms of their contribution to a firm's R&D activity during the most recent three years.

[12] Licensing agreements in biotechnology indicate that being basic is not an intrinsic barrier to licensing and closeness to science allows commercially relevant milestones to be specified using scientific terms, such as the characterization of a protein or the structure of a receptor.

[13] Technological rivals are defined as the number of U.S. competitors in the focus industry capable of introducing competing innovations that can effectively diminish the respondent's profits from an innovation. This variable represents each respondent's assessment of his or her focus industry conditions, and thus varies across respondents within an industry.

[14] The industry dummies are based on the following groupings: chemicals, petroleum and plastics (SIC 28, 29, 30, excluding 283), biotechnology and pharmaceuticals (SIC 283), computer and electronics (SIC 357 and 36), machinery (SIC 35, excluding 357), transportation (SIC 37), instruments (SIC 38, excluding 384), and medical instruments (SIC 384). Note that the results presented below are robust to the use of more disaggregated industry definitions.

4. Results

4.1. OLS Results

We first present single equation OLS results, reported in Table 3 (with and without interactions). The results are consistent with the theory developed in the previous section, suggesting that patent effectiveness has a positive and significant effect on patent propensity (Hypothesis 1b). We also find a positive and significant effect on licensing propensity, consistent with Hypothesis 1b, as well. The average elasticities of patenting and licensing, with respect to patent effectiveness, are about 0.5 and 0.6, respectively. The effect of the interaction between patent effectiveness and the complementary assets variable on licensing propensity is negative and significant, consistent with Hypothesis 2b.

4.2. Structural Estimates, Marginal Effects, and Elasticities

The reduced-form estimates have a number of shortcomings. They are inefficient because the residuals are heteroscedastic. The predicted outcome cannot be interpreted as a predicted probability because predictions could lie outside the (0–1) limits. Most of all, the estimated coefficients only provide qualitative information on the payoffs.[15] Thus, these estimates cannot directly test Hypotheses 1a and 2a. In contrast, in addition to being more precise, structural estimates allow us to disentangle the impact of the explanatory variables on $V_L - V_S$ and $V_P - V_S$, separately. This is an advance over the literature because it allows us to understand the channel through which intellectual property protection affects licensing.

Table 4 presents the structural estimates of (4-1) and (4-2), where we impose cross-equation restrictions, namely that $V_L - V_S$ and $V_P - V_S$ are present in the denominators in both equations and that the numerator in both equations shares the coefficients from $V_L - V_S$. We use the general method of moments (GMM), which allows for potential correlation across errors of the two equations and corrects for possible heteroscedasticity (cf. Gallant 1987, pp. 442–451). The estimates for $V_L - V_P$, reported in the second column of Table 4, are obtained as the difference between the estimates of $V_L - V_S$ and $V_P - V_S$.

For the control variables, Table 4 shows that measures of the codifiability of knowledge have a positive and significant effect on licensing payoffs, as expected. We also find that foreign, global, and public firms have substantially higher payoffs from

Table 3 Determinants of Patent and Licensing Propensities: OLS Estimates

	Patent propensity		Licensing propensity	
	I	II	I	II
Intercept	−0.06 (0.038)	−0.049 (0.039)	0.029 (0.026)	0.01 (0.026)
Patent effectiveness	0.495** (0.027)	0.466** (0.037)	0.091** (0.019)	0.138** (0.025)
Complementary assets	−0.037* (0.015)	−0.058* (0.024)	−0.027** (0.01)	0.007 (0.016)
Business unit employees (Log)	0.015** (0.004)	0.015** (0.004)	−0.004 (0.003)	−0.004 (0.003)
No. of technological rivals	−0.003* (0.002)	−0.003ᵃ (0.002)	0.001 (0.001)	0.0002 (0.001)
% basic R&D	−0.028 (0.124)	−0.036 (0.124)	0.304** (0.084)	0.318** (0.084)
Importance of medical/health science	−0.002 (0.010)	−0.003 (0.01)	0.017* (0.007)	0.018** (0.007)
Importance of basic science	0.001 (0.008)	0.002 (0.008)	0.011ᵃ (0.006)	0.01ᵃ (0.006)
Parent firm is global	0.038* (0.018)	0.037* (0.018)	−0.013 (0.012)	−0.011 (0.012)
Parent firm is foreign	0.029 (0.029)	0.03 (0.029)	−0.015 (0.02)	−0.016 (0.019)
Parent firm is public	0.061** (0.019)	0.06** (0.019)	0.002 (0.013)	0.002 (0.013)
Patent effectiveness × complementary assets		0.061 (0.052)		−0.1** (0.035)
Industry fixed effects (7)	Yes	Yes	Yes	Yes
N	757	757	757	757
Adj. R^2	0.44	0.44	0.14	0.15

Note. Standard errors are in parentheses.
**, *, ᵃ: Significantly different than zero at the 0.01, 0.05, and 0.10 confidence levels, respectively.

patenting for commercialization, $V_P - V_S$, but lower licensing payoffs, $V_L - V_S$. Technological rivalry has a negative impact on $V_P - V_S$ but a small and insignificant impact on $V_L - V_S$ and $V_P - V_L$. The industry effects (not reported) are jointly not significant in $V_P - V_S$. This is most likely because our science-specific dummies, especially the importance of medical/health science, which vary across respondents, pick up industry effects.[16] Industry effects are, instead, jointly significant in $V_P - V_S$, where the science dummies have no impact. As expected, chemical, pharmaceuticals, biotechnology, and medical instruments sectors are associated with higher payoffs for licensing patenting innovations, $V_L - V_P$.

The results, reported in Table 5a, provide strong support for Hypothesis 1a; that is, patent effectiveness

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[15] For instance, the right-hand side of the patenting equation can be thought of as reflecting the weighted average of $V_L - V_S$ and $V_P - V_S$, with firms with higher licensing propensities having higher-than-average weights on $V_L - V_S$, relative to firms with lower licensing propensities.

[16] Excluding biotechnology and pharmaceutical firms from the estimation does not change the results appreciably.

Table 4   GMM Structural Estimates of the System of Patent and Licensing Propensity Equations

	$V_L - V_S$ Licensing payoffs relative to not patenting	$V_L - V_P$ Licensing payoffs relative to patenting and not licensing	$V_P - V_S$ Patenting and not licensing payoffs relative to not patenting
Intercept	−4.164**	−0.914	−3.250**
	(0.563)	(0.670)	(0.307)
Patent effectiveness	2.564**	0.464	2.1**
	(0.481)	(0.534)	(0.256)
Complementary assets	−0.201	0.414	−0.615**
	(0.311)	(0.372)	(0.183)
Business unit employees (Log)	−0.021	−0.135*	0.115**
	(0.05)	(0.059)	(0.029)
Patent effectiveness × complementary assets	−0.590	−1.657*	1.067**
	(0.568)	(0.648)	(0.368)
No. of technological rivals	−0.007	0.023	−0.03*
	(0.02)	(0.026)	(0.013)
% basic R&D	2.822*	4.355**	−1.533
	(1.094)	(1.317)	(0.997)
Importance of medical/health science	0.268*	0.388**	−0.119
	(0.105)	(0.142)	(0.077)
Importance of basic science	0.246*	0.295*	−0.049
	(0.124)	(0.147)	(0.061)
Parent firm is global	−0.072	−0.426	0.355*
	(0.196)	(0.246)	(0.141)
Parent firm is foreign	−0.242	−0.696ª	0.454*
	(0.321)	(0.395)	(0.208)
Parent firm is public	0.103	−0.457	0.559**
	(0.256)	(0.343)	(0.164)
Industry fixed effects (7)	Yes	Yes	Yes
$N = 757$			

Notes. Standard errors are in parentheses. For estimation we used the SAS Proc Model GMM default option, which provides standard errors that are robust to potential heteroscedasticity and autocorrelation of the residuals. Adjusted R^2 is equal to 0.19 for the licensing equation and 0.43 for the patent propensity equation.

**, *, ª: Significantly different than zero at the 0.01, 0.05, and 0.10 confidence levels, respectively.

increases the patenting and licensing payoffs. The partial derivative of the net licensing payoff, $V_L - V_S$, with respect to patent effectiveness, is equal to 2.27, significant at the 1% level. The corresponding derivative of $V_P - V_S$ is 2.63, significant at the 1% level.

To examine Hypothesis 1b, we evaluate the marginal impact of patent effectiveness on licensing and patenting propensities, evaluated at the mean of the sample. The impact on patenting propensity is positive and significant at the 1% level, consistent with Hypothesis 1b, implying that a unit increase in patent effectiveness increases the probability of patenting by 0.47. Patent effectiveness, however, decreases the probability of licensing conditional on patenting by 0.06 and increases the unconditional

Table 5a   Marginal Effects on Licensing and Patenting Payoffs

	$V_L - V_S$	$V_L - V_P$	$V_P - V_S$
Hypothesis 1a			
Patent effectiveness	2.27**	−0.36	2.63**
	(0.33)	(0.36)	(0.20)
Hypothesis 2a			
Patent effectiveness × complementary assets	−0.59	−1.66*	1.07**
	(0.56)	(0.65)	(0.37)

Table 5b   Marginal Effects on the Probabilities of Patenting and Licensing

	Probability of licensing	Probability of licensing conditional on patenting	Probability of patenting
Hypothesis 1b			
Patent effectiveness	0.08**	−0.06	0.47**
	(0.01)	(0.06)	(0.03)
Hypothesis 2b			
Patent effectiveness × complementary assets	−0.06*	−0.25*	
	(0.03)	(0.11)	

Notes. Standard errors are in parentheses. Marginal effects and elasticities are obtained using the GMM estimates, evaluated at the mean of the respective sample.

**, *, ª: Significantly different than zero at the 0.01, 0.05, and 0.10 confidence levels, respectively.

probability of licensing by 0.08 (significant at the 5% level). In other words, more effective patents *do* lead to more licensing, but this is mostly driven by the indirect effect of patent effectiveness on the probability of patenting. This is more easily seen, noting that Elasticity of Pr(Lic) = Elasticity of Pr(Lic | Pat) + Elasticity of Pr(Pat). The elasticity of the conditional probability is −0.08, and the elasticity of patenting is 0.51, so that the elasticity of the probability of licensing with respect to (w.r.t.) patent effectiveness is 0.43.

The central result of this paper relates to the impact of the interaction between patent effectiveness and complementary assets on licensing payoffs and probabilities, related to Hypotheses 2a and 2b. The structural estimates of the parameter related to the interaction term, shown in Table 4, clearly indicate a negative and significant impact on $V_L - V_P$ and a positive and significant impact on $V_P - V_S$. These results confirm Hypothesis 2a, namely that firms with specialized complementary assets derive greater value from more effective patent protection, but not through licensing.

The cross-partial effect of patent effectiveness and complementary assets on the licensing probabilities is shown at the bottom of Table 5b. To compute this effect, we first divide the sample into firms with high and low specialized complementary assets (according to our measure). For each group, we then compute the marginal effects of patent effectiveness on

the respective licensing probabilities evaluated at the group mean. Consistent with Hypothesis 2b, we find that licensing is less responsive to patent effectiveness, both for patented innovations and for all innovations, for firms with specialized complementary assets relative to firms that do not possess them (the difference is significant at the 5% level). Because we control for business unit size, these results are not merely reflecting scale effects and suggest that the ownership of specialized complementary assets critically conditions the impact of patent protection on licensing.

Recall that Hypothesis 2b does not require that an increase in patent effectiveness actually decreases licensing for firms with high complementary assets, but merely that any increase be smaller than that for firms with low complementary assets, although such a result is obviously consistent with it. Table 6, which reports the marginal effects and elasticities of patent effectiveness on the licensing probabilities, shows that firms with high specialized complementary assets and higher effectiveness of patent protection are more likely to patent but less likely to license their patented innovations than firms with high specialized complementary assets but low patent effectiveness. Firms with low specialized complementary assets and high patent effectiveness are more likely to license, but they are also more likely to license their patented innovations than firms with low specialized complementary assets and low patent effectiveness.

In sum, the results suggest that firms with specialized complementary assets react to stronger patent protection by patenting more, but using the patents to enhance the payoff from commercialization. Firms lacking specialized complementary assets also respond by increasing patenting but are more likely to use patents as a basis for licensing.

5. Sensitivity Analysis[17]
We now evaluate the sensitivity of our results to possible endogeneity and alternative specifications.

5.1. Potential Endogeneity of Complementary Assets
We have assumed, in the spirit of the resource-based theory, that complementary assets are exogenous. However, it is possible that unobserved factors that reduce licensing costs or increase licensing payoff may also reduce complementarity between manufacturing and R&D.[18] To address this concern, we

[17] See the online appendix for further details of results presented in this section.

[18] In a linear specification, this would imply that the coefficient on complementary assets would have a negative bias in the licensing equation. In a nonlinear specification such as ours, the bias cannot be judged as readily.

Table 6   The Impact of Patent Protection on Licensing Probabilities by Complementary Assets (Hypothesis 2b)

	Marginal effects and elasticities w.r.t. patent effectiveness of			
	Probability of licensing		Probability of licensing conditional on patenting	
	Marginal effect	Elasticity	Marginal effect	Elasticity
Complementary assets				
Low	0.11** (0.03)	0.62	0.07 (0.08)	0.14
High	0.05** (0.01)	0.24	−0.18* (0.08)	−0.30
Total	0.08** (0.01)	0.43	−0.06 (0.06)	−0.08

Notes. Standard errors are in parentheses. Marginal effects and elasticities are obtained using the GMM estimates, evaluated at the mean of the respective sample.

**, *, [a]: Significantly different than zero at the 0.01, 0.05, and 0.10 confidence levels, respectively.

instrument for the presence of complementary manufacturing assets using a dummy variable indicating whether the R&D lab is located near a production facility. Thus, if one accepts that the location of the lab is a long-term decision, colocation between R&D and manufacturing is a source of exogenous variation in the frequency of interactions between R&D and manufacturing.[19]

As Tables 7a and 7b show, all our main results are confirmed, although the standard errors are typically larger. The interaction between complementary assets and patent effectiveness continues to have a negative and significant effect on $V_L - V_P$ and a positive and significant effect on $V_P - V_S$ (Columns VI and X, Table 7a). The marginal effect of patent effectiveness on licensing propensity is positive and decreases from 0.09 to 0.06 between firms with low and high specialized complementary assets (Column II, Table 7b). Similarly, the marginal effect of patent effectiveness on the share of licensing in patented innovations is lower for firms with low specialized complementary assets (Column VI, Table 7b).

5.2. Endogeneity of Patent Effectiveness and Other Possible Biases
It is possible that R&D managers from labs with high patent propensity also tend to report higher patent effectiveness to "justify" their patenting behavior and related costs. However, even after controlling for industry-fixed effects, the average patent effectiveness score when the respondent is from a non-R&D function (about 13% of the sample) is only 0.002 lower than the average score of respondents from the R&D lab, a very small and insignificant difference.

[19] The correlation coefficient between complementary assets and colocation is 0.2, significant at the 1% level.

Table 7a   **Marginal Effects on Licensing and Patenting Payoffs Using Instrumental Variables for Patent Effectiveness and Complementary Assets (Hypothesis 2a)**

	$V_L - V_S$				$V_L - V_P$				$V_P - V_S$			
	I Exog. θ and ρ	II Endog. ρ	III Endog. θ	IV Endog. θ and ρ	V Exog. θ and ρ	VI Endog. ρ	VII Endog. θ	VIII Endog. θ and ρ	IX Exog. θ and ρ	X Endog. ρ	XI Endog. θ	XII Endog. θ and ρ
Patent effectiveness (θ) × complementary assets (ρ)	−0.59 (0.56)	−0.25 (1.71)	−0.69 (1.03)	−2.78 (2.29)	−1.66* (0.65)	−3.08 (2.17)	−0.86 (1.5)	−4.97[a] (2.82)	1.07 (0.37)	2.83[a] (1.51)	0.17 (1.15)	2.19 (2.1)

Table 7b   **IV Estimates of the Impact of Patent Effectiveness (θ) on Licensing Probabilities by Complementary Assets (ρ) (Hypothesis 2b)**

	Marginal effects w.r.t. patent effectiveness (θ) of							
	Probability of licensing				Probability of licensing patented innovations			
	I Exog. θ and ρ	II Endog. ρ	III Endog. θ	IV Endog. θ and ρ	V Exog. θ and ρ	VI Endog. ρ	VII Endog. θ	VIII Endog. θ and ρ
Complementary assets (ρ)								
Low	0.11** (0.0)	0.09** (0.03)	0.14** (0.03)	0.13** (0.03)	0.07 (0.08)	0.09 (0.1)	−0.03 (0.22)	0.08 (0.17)
High	0.05** (0.01)	0.06* (0.03)	0.07** (0.02)	0.07 (0.05)	−0.18* (0.08)	−0.47 (0.36)	−0.14 (0.15)	−0.95[a] (0.58)
Total	0.08** (0.01)	0.07** (0.02)	0.10** (0.02)	0.11** (0.03)	−0.06 (0.06)	−0.16 (0.08)	−0.09 (0.16)	−0.29 (0.25)

Note. Standard errors are in parentheses.

**, *, [a]: Significantly different than zero at the 0.01, 0.05, and 0.10 confidence levels, respectively.

A different concern is that the reported patent effectiveness simply reflects reporting biases (e.g., managers who, for some reason, favor patenting also report patents to be more effective) or differences in knowledge base or technical opportunity. To address this, we also estimated a specification instrumenting for patent effectiveness, using two sets of instruments. One is the industry average of patent effectiveness at the level of the *primary industry of the respondent's parent firm*.[20] Patent effectiveness, a self-reported measure of the net benefits from patenting, reflects both "endogenous" variation in the strength of patents, such as the patentability of technology, as well as "exogenous" variation related to the business unit's parent firm's patenting culture or to the shared resources available to enforce patents at the firm level. It is the latter that we hope to capture through the instrument. The instrument is valid in the sense that the effectiveness of patents in the industry of the parent firm should not have any *direct* impact on patenting or licensing payoffs of the business unit and should only have an *indirect effect* through patent effectiveness.

Similarly, insofar as location is a long-term choice, differences in the litigation environment across federal districts should affect behavior only through how effective managers perceive patents to be. We use the average time to resolution of patent cases during 1990–1993 and its standard deviation, the average success rate of patent holders, and the number of terminated patent cases in the district court where the respondent lab is located as additional instruments for patent effectiveness.[21]

Tables 7a and 7b present the estimates for payoffs and propensities, respectively, where we instrument for patent effectiveness and complementary assets. The results are qualitatively unchanged, although the standard errors are larger.

5.3. Additional Specifications

Controlling for R&D. We measure licensing propensity as the percentage of R&D invested with the objective of licensing. For a given share of innovations

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[20] Roughly half of the business units belong to an industry different from the primary industry of the parent firm.

[21] Source: "Federal Court Cases: Integrated Data Base, 1970–1994," Federal Judicial Center, Interuniversity Consortium for Political and Social Research. The time to resolution is computed as the number of months between the date on which a case was filed in a district court and its termination by any means (e.g., settlement, dismissal, judgment).

that are licensed, the percentage of R&D invested for licensing will decrease with the level of R&D. Similarly, a firm that has more innovations than it can develop in house will be more likely to license. However, controlling for this possibility by including R&D or R&D intensity (R&D/sales) as controls does not change the results. Indeed, R&D or R&D intensity has only a small and statistically insignificant impact on patenting and licensing payoffs.

Sequential Decision Making. Our model assumes that the licensing and patenting decisions are taken simultaneously. However, some patenting decisions may be made before the licensing opportunities have materialized. We also estimated a specification where the licensing decision is made after the patenting decision and obtained similar results to those presented here (see the online appendix). The estimated variance of the difference between random components of the payoffs is small, which suggests that our firm-level cross-sectional data are poorly suited to the task of estimating a model of sequential decision making. The analysis of the sequential stages of patenting and licensing decisions requires analysis with different data and is left for future research.

Correlation in Errors. Our model assumes that the unobserved, stochastic components in payoffs are mutually uncorrelated. We also estimated two different specifications that relax this assumption—the nested logit and the multinomial probit specifications (estimated using proportions and the GMM method). The estimated correlation coefficient between unobserved errors (e.g., allowing correlation between V_L and V_P, or V_P and V_S) is not significantly different from zero, suggesting that the main results of the paper are robust to relaxation of such assumption.

Alternatively, one can estimate the equation for the probability of licensing conditional on patenting (3-3) as a single equation, using the observed licensing propensity divided by the patent propensity as a dependent variable. If V_L and V_P were correlated, the conditional probability would be a function of $(V_L - V_P)/(1 - \sigma)$, with σ reflecting the strength of the correlation and varying between 0 and 1 (Maddala 1983, pp. 70–72). The estimated coefficient of the interaction term in the single structural equation is still negative, as predicted by Hypothesis 2a, but is statistically insignificant. The fall in precision in the estimates is likely to be due to the exclusion of the nonpatentees, or about 25% of the sample.

Within-Group Estimation. We also estimated the model within the groups of firms with low and high complementary assets, allowing all coefficients to vary across groups, and found that the central result of the paper, summarized in Table 6, is even stronger. The estimated elasticity of licensing w.r.t.

patent effectiveness is 0.7 (0.02) for low (high) complementary asset firms. Similarly, the elasticity of the share of licensing in patented innovations is 0.2 (−0.5) for low (high) complementary asset firms.

5.4. Licensing Without Patents
We further analyzed the 25 cases that involved positive licensing propensity but zero patent propensity. Two-thirds of these involved public firms, for which 10Ks and annual reports were available, and a closer examination revealed that most of these firms typically did not engage in technology licensing, but may be licensing software or trademarks. In a small number of cases, it appeared that firms had applied for patents, but not during 1991–1993, the survey time frame, which implies measurement error as the cause of the apparent anomaly. Including those 25 observations in the sample and assigning them a null propensity to license does not change our results. Although, in principle, firms that patent may still license some of their unpatented innovations, data limitations do not allow us to investigate this possibility further.

6. Conclusion
The ability of firms to appropriate the returns from their innovations is a key driver of the willingness of firms to invest in innovative activity. In recent years, some firms appear to have resorted to technology licensing as a way of appropriating the returns. But even when licensing is feasible, it is well known that the market for technology suffers from various imperfections. Effective patents can ameliorate some of these imperfections. However, more effective patents also increase the payoff from commercialization, making it important to quantify the impact of patent effectiveness on licensing.

We analyze how patenting and licensing strategies are related and how patent effectiveness and complementary assets condition the use of patenting and licensing by firms to appropriate rents from innovation. We find that increases in patent effectiveness indirectly affect licensing by increasing the propensity of firms to seek patent protection. However, this also decreases the proportion of patented innovations that are licensed, implying a smaller net increase in licensing propensity.

Our results highlight the importance of the interaction between patent effectiveness and a firm's ownership of specialized complementary assets in conditioning licensing decisions. We argue that insofar as complementary assets are difficult to acquire or imitate, stronger patent protection will increase the payoff to commercialization relative to licensing. Indeed, we find that higher patent effectiveness elicits much larger increases in licensing from firms lacking specialized complementary assets.

Thus, our study also helps reconcile conflicting empirical evidence of the impact of patent protection on licensing. For instance, studies undertaken using samples of small firms or start-ups, which are less likely to have specialized complementary assets (e.g., Gans et al. 2002), are also more likely to find a stronger impact of patent effectiveness on licensing. Conversely, studies of cross-national technology licensing by large multinationals are less likely to find an impact of patent effectiveness on licensing (e.g., Fosfuri 2004b). Similarly, studies focusing on patented innovations are more likely to find only a small impact of the strength of patents on licensing, because they neglect the effect on the propensity to patent.

These results point to the need to better understand the interplay between different strategic instruments available to firms in their quest to appropriate rents from innovation. In particular, it seems important to move beyond the short-term adjustment model inherent in the present study by relaxing the assumption of exogenous investments in complementary assets. For instance, although our findings are consistent with the view that technology start-ups lacking manufacturing or marketing assets should license their innovations when patent protection is effective, other options may be available. Limited access to such assets could be obtained through alliances with established partners, as in pharmaceuticals, or through independent foundries, as in semiconductors. Alternatively, a start-up may decide to invest in in-house manufacturing and marketing capability, as firms such as Genentech and Amgen appear to have done. When a strategy of acquiring complementary assets is superior to one of licensing or one of alliances is thus an important area for future research. Our findings point to the importance of understanding better when the long-term industry configuration can feature vertical "technology specialists" (Arora and Gambardella 1994) and when, instead, innovators must battle with incumbents.

An online appendix to this paper is available on the *Management Science* website at http://mansci.pubs.informs.org/ecompanion.html.

Appendix. A Model of the Determinants of Licensing

PROOF OF HYPOTHESES 1A AND 1B. Let θ represent an index of patent effectiveness. As argued in the text, it is intuitive that increases in θ increase both $V_L - V_S$ and $V_P - V_S$. The impact on $V_L - V_P$ is, however, ambiguous (Hypothesis 1a).

$$\Pr(\text{Pat}) = \frac{1}{1+B}, \quad B = \frac{1}{\exp(V_P - V_S) + \exp(V_L - V_S)}.$$

Because both $(V_L - V_S)$ and $(V_P - V_S)$ are nondecreasing in θ, it follows that B is decreasing in θ, and so $\Pr(\text{Pat})$ is increasing in θ.

$$\frac{d\Pr(\text{Lic})}{d\theta}$$

$$= \frac{\Pr(\text{Lic})}{A}\left(\exp(V_P - V_S)\frac{d(V_L - V_P)}{d\theta} + \frac{d(V_L - V_S)}{d\theta} - 1\right),$$

$$A = \exp(V_P - V_S) + \exp(V_L - V_S) + 1.$$

Because the sign of $d(V_L - V_P)/d\theta$ is ambiguous, so is the overall expression. Similarly, it also follows that the share of licenses in patented innovations could either increase or decrease with respect to patent effectiveness. This demonstrates Hypothesis 1b. □

PROOF OF HYPOTHESIS 2A. By definition, $dV_S/d\theta = 0$, because patent effectiveness can have no effect if the innovation is not patented, and hence $d^2 V_S/d\rho d\theta = 0$. Similarly, $dV_L/d\rho = 0$ because if the innovation is licensed, what matters is the complementary assets of the licensee, not those of the innovator. In the text, we argued that $d^2 V_P/d\rho d\theta > 0$ because stronger patents are more valuable to firms owning the specialized complementary assets. In what follows, the intuition is formalized using standard models of both product and process innovations with asymmetric firms and imitation.

Process Innovation. In a standard two-stage model of R&D competition (cf. d'Aspremont and Jacquemin 1988, De Bondt et al. 1992, and Ceccagnoli 2005), in stage 1 two firms (i, j) choose the amount of cost reducing R&D, the cost of which is quadratic in R&D, and in stage 2, firms compete à la Cournot in a homogeneous product market with linear demand $(p = 1 - Q)$. Marginal costs are equal to $c_i = c - \rho_i - R_i - (1 - \theta_j)R_j$ for firm i, where ρ_i is an index of firm i complementary assets, and $(1 - \theta_j)$ represents the fraction of rival j's R&D, which is imitated by firm i, thus reducing firm i's costs, with $0 \leq \theta_j \leq 1$. A greater θ_j reflects stronger patent protection for firm j. Profits from commercialization and patenting for firm i are equal to

$$V_i^P = (q_i^c)^2 - \tfrac{1}{2}R_i^2, \quad \text{with } q_i^c = \tfrac{1}{3}[1 - 2c_i + c_j].$$

It is easily verified that, for any given level of R&D,

$$\frac{\partial^2 V_i^P}{\partial \rho_i \partial \theta_i} = \tfrac{4}{9}R_i > 0,$$

which formalizes Hypothesis 2a for the case of process innovations.

Product Innovation. An innovation may also be quality improving (rather than merely cost reducing). This can be dealt with using a standard model of vertical differentiation (e.g., Shaked and Sutton 1982). The buyer's utility function is $vx - p$, where x is the quality of the product, p is the price, and v is the buyer's willingness to pay for quality. Typically, v is assumed to be uniform, and for simplicity, we let it be uniform between $[0, 1]$. Let the innovator's quality be x and the rival's quality be x', $x > x'$. The (constant) marginal costs of production are, respectively, c and c', and the prices chosen are p and p', respectively. Let $\Delta x = x - x'$, and define Δp and Δc similarly. Assuming that the entire market is covered, the demand for the innovator is given by $1 - v^*$, where $v^* = \Delta p / \Delta x$. We assume that the innovator can choose the quality level by incurring a product R&D cost $G(x)$, $G_x > 0$, $G_{xx} > 0$, so that higher quality requires increasingly higher product R&D. Complementary commercialization assets, ρ, reduce the "cost of achieving high quality," i.e., $G_\rho < 0$, $G_{\rho x} < 0$. We also assume that through spillovers, rivals can partially imitate the innovator, so that x' is an increasing function of x. Unless spillovers are perfect, the increase in the rival's quality should be less than the increase in the innovator's quality. Further, an increase in patent effectiveness, by reducing spillovers, reduces x'. Specifically, we assume that $\partial x' / \partial x = 1 > \gamma > 0$, and $\partial x' / \partial \theta < 0$. The profit function for the innovator is given by $(p - c)(1 - v^*) - G(x)$, and the innovator chooses price and quality to maximize profits. Let $\pi(\theta, \rho)$ represent the maximized profit function. Then,

$$\frac{\partial \pi}{\partial \rho} = -G_\rho, \qquad \frac{\partial^2 \pi}{\partial \rho \partial \theta} = -G_{x\rho} \frac{\partial x}{\partial \theta}.$$

Because $G_{\rho x} < 0$, a necessary and sufficient condition for $\partial^2 \pi / \partial \rho \partial \theta > 0$ is $\partial x / \partial \theta > 0$, i.e., the innovator's quality increases with patent effectiveness. We show below that this is indeed true.

Case 1: *Rivals Are a Competitive Fringe.* We assume that imitators are a competitive fringe so that they price at marginal cost, i.e., $p' = c'$. Assuming an interior optimum for x (so that $\pi_{xx} < 0$), it follows that $(\partial x / \partial \theta) = (\partial^2 \pi / \partial x \partial \theta) / (-\pi_{xx})$. Thus, the sign of $(\partial x / \partial \theta)$ is the same as the sign of $\partial^2 \pi / \partial x \partial \theta$. Substituting in the optimum price, one can write the innovator's profits, $\pi = \Delta x / 4 + (\Delta c)^2 / 4\Delta x - \Delta c / 2 - G(x)$. Thus, $\partial \pi / \partial x = (1 - \gamma)/4\{1 - (\Delta c)^2 / (\Delta x)^2\} - G_x$, so $\partial^2 \pi / \partial x \partial \theta = [(1 - \gamma)(\Delta c)^2 / 2(\Delta x)^3](-\partial x' / \partial \theta) > 0$.

Case 2: *Strategic Price Competition.* We continue to assume that the innovator selects quality, and this also determines the rival's quality through spillovers. Unlike Case 1, the innovator and its rival set prices strategically. Thus, we have a two-stage game, wherein the innovator chooses the quality level (i.e., product R&D level), determining its quality and that of its rival, and in stage 2, both compete by setting prices. One can show that in the second stage, the innovator's profits, π, can be written as $\pi = \Delta x / 9 + (\Delta c)^2 / 9\Delta x - 8\Delta c / 9 - G(x)$. Note that this has the same form as the profit function in Case 1, and thus it is easy to show that $\partial^2 \pi / \partial x \partial \theta > 0$. This formalizes Hypothesis 2a for the case of product innovation. □

PROOF OF HYPOTHESIS 2B. As noted in the text, the relationship between payoffs and behavior is nonlinear so that second-order impacts of variables on payoffs do not translate directly into impacts on behavior such as licensing propensity. Note that

$$\frac{d^2 \Pr(\text{Lic})}{d\rho d\theta} = \frac{1}{\Pr(\text{Lic})} \frac{d\Pr(\text{Lic})}{d\theta} \frac{d\Pr(\text{Lic})}{d\rho}$$
$$+ \Pr(\text{Lic}) \left[\frac{d\Pr(\text{Lic})}{d\rho} \left(\frac{dV_P}{d\theta} - \frac{dV_L}{d\theta} \right) \right.$$
$$\left. - \frac{dV_P}{d\theta} \frac{d\Pr(\text{Pat})}{d\rho} + [\Pr(\text{Lic}) - \Pr(\text{Pat})] \frac{d^2 V_P}{d\rho d\theta} \right].$$

The first term on the right-hand side is indeterminate in theory but negative in our empirical results. The second term depends on three subterms inside the square brackets, of which only the third is predicted to be negative by our theory (by Hypothesis 2a); the other two are indeterminate. Given that $\Pr(\text{Lic})$ is always lower than $\Pr(\text{Pat})$, a sufficient condition for $d^2\Pr(\text{Lic})/d\rho d\theta$ to be negative is that the positive interaction effect, $d^2 V_P / d\rho d\theta$, is sufficiently strong.

The impact on the share of licensing in patented innovations is also indeterminate in theory and becomes negative if the interaction effect between patent effectiveness and complementary assets presented in Hypothesis 2a is sufficiently strong:

$$\frac{d^2 \Pr(\text{Lic} \mid \text{Pat})}{d\theta d\rho} = \frac{d\Pr(\text{Lic} \mid \text{Pat})}{d\rho} \left(\frac{dV_L}{d\theta} - \frac{dV_P}{d\theta} \right)$$
$$\cdot [\Pr(\text{NotLic} \mid \text{Pat}) - \Pr(\text{Lic} \mid \text{Pat})]$$
$$- \Pr(\text{Lic} \mid \text{Pat}) \Pr(\text{NotLic} \mid \text{Pat}) \left(\frac{d^2 V_P}{d\theta d\rho} \right).$$

The first term of this difference is indeterminate in theory, although our empirical results imply that it is positive but small (insignificantly different from zero). The second term is positive, because the cross-partial is positive. Therefore, a sufficient condition for $d^2\Pr(\text{Lic} \mid \text{Pat})/d\rho d\theta$ to be negative is that the positive interaction effect, represented by $d^2 V_P / d\rho d\theta$, is sufficiently strong, so that the second term outweighs the first. □

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