Strategic Management Journal
Strat. Mgmt. J., **34**: 404–425 (2013)
Published online EarlyView in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.2020
Received 20 May 2011; Final revision received 3 September 2012

THE COST OF INTEGRATING EXTERNAL TECHNOLOGIES: SUPPLY AND DEMAND DRIVERS OF VALUE CREATION IN THE MARKETS FOR TECHNOLOGY

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A classic question faced by technology suppliers and buyers is whether to compete in the product markets or to cooperate through licensing. We address this question by examining an important, demand-side barrier to licensing—the buyers' cost of integrating a licensed technology. We argue that this cost can be affected by suppliers' knowledge transfer capabilities, buyers' absorptive capacity, and the cospecialization between R&D and downstream activities in the buyers' industries. Following this argument and a stylized bargaining model, we hypothesize that the supplier's knowledge transfer capability stimulates licensing. Moreover, the importance of this capability increases when licensing to industries where potential buyers have weak absorptive capacity or R&D and downstream activities are cospecialized. We find support for our hypotheses using a panel dataset of small 'serial innovators.' Copyright © 2012 John Wiley & Sons, Ltd.

INTRODUCTION

Recent decades have witnessed substantial expansion of markets for technology in which firms trade technology through formal contracts such as licensing (Arora and Gambardella, 2010). Indeed, between 1996 and 2006, the value of technology exchanges within Organisation for Economic Co-operation and Development (OECD) nations as a percentage of gross domestic product (GDP) increased by 63 percent (OECD, 2009). The result is an improved division of labor between the production of and the use of technology. Despite this outcome, technology licensing is still not a central activity in corporate strategy and is limited to certain industries such as biopharmaceuticals and electronics (Arora, Fosfuri, and Gambardella, 2001).

Understanding what limits and facilitates licensing has been an important topic of recent strategy research. However, much of the current literature has focused primarily on the supply-side factors and does not adequately account for the demand side (Arora and Gambardella, 2010). For instance, the literature has suggested that critical factors of licensing include the suppliers' costs of acquiring complementary downstream assets, the strength of intellectual property rights (IPR) in protecting the suppliers (Arora and Ceccagnoli, 2006; Gans and Stern, 2003), and the transaction costs caused by incomplete contracting or undesired leakage of information (Arora *et al*., 2001; Fosfuri, 2006; Gambardella, Giuri, and Luzzi, 2007; Williamson, 1979). Except for the transaction costs incurred by both suppliers and buyers, other major licensing concerns lie primarily on the side of the technology

Keywords: technology licensing; technology integration costs; cospecialized complementary assets; absorptive capacity; knowledge transfer capabilities
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suppliers. A deeper understanding of licensing, however, requires a more explicit analysis of the issues facing the potential buyers.

In this study, we develop and estimate a stylized model that explicitly incorporates the demand-side incentives to commercialize technology by focusing on an important barrier to licensing—the cost for potential buyers to integrate external technology into their products and value chains. As an example of such integration costs, Apple Inc. made a substantial investment in the changes to the microprocessor technology that it licensed from ARM Holdings for its iPad 2.[1] Examining such integration costs allows us to delve into the black box of the transaction costs of licensing—the transaction costs are not only caused by imperfect contracts but also by the *real* cost of transferring technology across firm boundaries. We argue that this integration cost is conditioned by both supply- and demand-side factors. First, the suppliers' knowledge transfer capability is an important factor in lowering buyers' integration costs (Contractor, 1981; Teece, 1977), and is thus hypothesized as a key driver for licensing. Second, integration costs can be lowered by buyers' absorptive capacity. Given this, we hypothesize that the suppliers' knowledge transfer capabilities are less critical when licensing to an industry in which the typical potential buyer has stronger absorptive capacity (e.g., Apple, Samsung, and Intel, all of which bought ARM's technology). Third, drawing on the economics and the management literature (Arora and Ceccagnoli, 2006; Milgrom and Roberts, 1990; Teece, 1986), we argue that integration costs are higher when complementary downstream activities such as manufacturing and marketing are more cospecialized with research and development (R&D). Essentially, cospecialization between R&D and downstream activities reduces efficiency when it comes to commercializing a technology across the boundaries of firms. This inefficiency, however, can be overcome by suppliers' knowledge transfer capabilities. Thus, we hypothesize that the suppliers' knowledge transfer capabilities are more critical when licensing to an industry that features higher cospecialization between R&D and downstream activities.

We find empirical support for our hypotheses using a representative sample of U.S. technology-based firms with fewer than 500 employees. This sample is derived from the Small Business Administration (SBA) database, which contains patenting information on the population of U.S. technology-based firms with fewer than 500 employees that were able to sustain innovation beyond the first invention upon which the firm was founded (Hicks and Hegde, 2005). We integrated this dataset with information gathered from multiple additional sources, including the SDC Platinum alliances database available from Thomson Reuters, United States Patent and Trademark Office (USPTO) data, Compustat, and the Carnegie Mellon Survey on industrial R&D. The result is a dataset that includes annual information on the licensing strategies of a set of 519 small, patent-intensive, public and private U.S. companies with patents applicable across a broad range of 38 application industries over a time period from 1996 to 2007. We observe the number of licensing deals made by each technology supplier in each of its potential application industries in each year.

Our empirical estimation critically relies on the identification of sample firms' application industries. We did so by matching each firm's patent technology classes to that of the Standard Industrial Classification (SIC) code system. This allowed us to identify application industries that are not conditional on the technology being licensed to the industries. This method also allows us to exploit the cross-industry variation in our measures of cospecialization and absorptive capacity, which are measured at the level of the application industry. These measures, along with a measure of supplier knowledge transfer capability that varies across firms, application industries, and time, provide a key source of identification to estimate our model.

THEORY AND PROPOSITIONS

In order to illustrate the role of both supply- and demand-side incentives to commercialize technology, we used a stylized game theory model in which a small, technology-based firm ('supplier,' 'seller,' or 'licensor') has inventions that can potentially be commercialized in an industry ('application industry'). The firm may exploit opportunities in this industry through licensing,

[1] http://www.eetimes.com/electronics-news/4215094/A5–All-Apple–part-mystery?pageNumber=0 (31 August 2012).

DOI: 10.1002/smj

which means selling the inventions to the incumbent firms of this industry ('buyers,' 'incumbents,' or 'licensees'). The incumbents can then incorporate the inventions into their final products; in return, the supplier may earn licensing revenues. Alternatively, the supplier may enter the industry on its own by acquiring the downstream complementary assets necessary to commercialize the inventions. The latter entails the investment of forward integration. The supplier may also decide to shelve the inventions and not commercialize them. This choice reflects a case where commercializing the technology would not generate positive profits. Since including this choice does not change our main predictions, we leave out this third choice and include it only in our online appendix and illustrate the simplified model here to better focus on the underlying intuitions.

The decision tree in Figure 1 characterizes the expected payoffs from the decision with reference to both the supplier and a potential buyer.

This decision tree incorporates some of the key drivers of the licensing/forward integration decision highlighted by prior research. First is the cost (A) for the technology supplier to acquire complementary assets (manufacturing, sales, and service) if it chooses forward integration. When complementary assets are costly to acquire, entrepreneurial firms are more likely to avoid duplicating these assets and ally with incumbents that already possess these assets (Gans, Hsu, and Stern, 2002; Teece, 1986). Furthermore, the costs (A) are a function of asset cospecialization (k), which is the extent to which commercialization requires cospecialized complementary assets, such as specialized knowledge generated during development, manufacturing, and marketing that entails a mutual dependence between development and commercialization activities. Such cospecialized assets are typically developed over time and are hard to acquire in the market, thus increasing the sunk costs of entry (Gans and Stern, 2003; Teece, 1986).

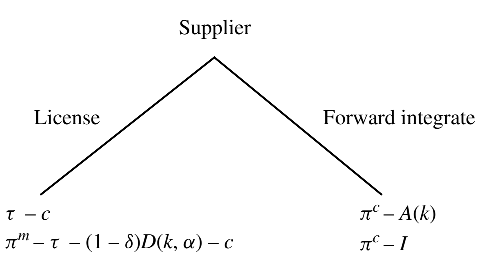

Figure 1. Decision tree

Other parameters that influence the licensing decision include the profits from commercializing the technology, licensing fees, and the classic transaction costs (e.g., Gans *et al.*, 2002). Specifically, if the negotiation between an incumbent and the supplier succeeds, the incumbent commercializes the technology and earns π^m from the marketplace. The supplier, in turn, earns a licensing revenue τ paid by the incumbent. The parties incur the transaction cost c including the costs of negotiating and enforcing the license.[2] If the supplier decides to integrate vertically into the application industry, the supplier faces competition from the incumbent in the product market and earns π^c from competing in the product market. The incumbent earns a profit of $\pi^c - I$, with I denoting the incumbent's cost to generate an alternative technology for the market. I depends on the R&D productivity of the incumbent. For simplicity, we assume that the incumbent also earns a profit of π^c from competing with the supplier. Because of competition, π^c is smaller than π^m.

In this simplified framework, licensing will take place if the gains from trade outweigh the costs. As in Gans and colleagues' (2002) model, the gains from the trade are caused by the avoidance of product market competition and the avoidance of duplicative costs incurred by acquiring downstream assets. However, a distinguishing feature of our model is that the gains from licensing can also be reduced by the integration costs incurred by buyers, which we explain in detail below.

Integration costs in licensing and knowledge transfer capability

The key difference from Gans *et al.*'s (2002) model is that we introduce the integration cost for licensing, D, and a capability parameter of the supplier (i.e., δ, the supplier's knowledge transfer capability). Integration cost is defined as

[2] We supposed for simplicity that the transaction costs of licensing are not a function of k. Indeed, to the extent that cospecialization entails relationship-specific investments by the parties, it also creates the classic threat of holdups, which may reduce the incentives for licensing. However, since this is not the key mechanism driving our results, we kept the model as simple as possible and noted that relaxing this assumption does not affect our main predictions.

DOI: 10.1002/smj

the expected cost for incumbents in an application industry to integrate the supplier's technology. Certainly, technology-specific factors can contribute to this cost, such as the technology's maturity or its need for expensive equipment. What is less obvious, but critical to the integration cost, is the nature of the demand side. Indeed, two critical demand-side characteristics will affect the integration cost. The first is α, that is, the absorptive capacity of the incumbent or potential buyer. The absorptive capacity is a firm's ability to acquire, assimilate, and exploit knowledge created outside its organization (Cohen and Levinthal, 1989). High absorptive capacity is often the result of continuous R&D targeted toward monitoring and learning about new developments created by other organizations (Cohen and Levinthal, 1989). Organizational routines may also be developed to assess and exploit external technologies (Lane, Koka, and Pathak, 2006). If a potential buyer has a weak absorptive capacity as a result of little investment in the monitoring of and learning from external developments or a lack of routines for such activities, we can expect that the buyer's cost of integrating external technologies will be high.

The second source of integration cost is k, the degree of cospecialization between R&D and downstream activities in the application industry. For example, cospecialization exists when a new product design requires specialized manufacturing knowledge and when a change in manufacturing needs to be compatible with the specialized product design (Teece, 1986). In other words, with cospecialization, an innovation and its subsequent commercialization are intertwined, requiring ongoing mutual adjustments (Kline and Rosenberg, 1986; Teece, 1992). For industries that feature such cospecialization, successful commercialization often requires proximate, tight, and frequent communication links between personnel from R&D and personnel from manufacturing or marketing. Such interdependencies, highlighted by a number of scholars, give rise to complementarity across activities in the value chain (Kline and Rosenberg, 1986; Milgrom and Roberts, 1990). When these interdependent and complementary activities are performed in two separate firms, coordination costs arise, which increase the cost of integrating the focal technology into the buyer's value chain. These inefficiencies go beyond the potential for holdups that arise as a consequence of relationship-specific investments.

The second novel component of our model is δ, the supplier's knowledge transfer capability. Many technology-based firms have cutting-edge technology but fail to transfer it effectively to buyers (Shane, 2004). We define a supplier's knowledge transfer capability as its ability to identify and communicate the value of its technology and to transfer the necessary know-how to potential buyers. Knowledge transfer has an important firm-level component since it entails organizational processes, often as a result of past experience, that effectively facilitate the identification of buyers' special needs and the communication of the needed know-how to buyers (Kogut and Zander, 1993). The ability to transfer knowledge has been found to be a highly important component in other settings, including the international expansion of multinational firms (Martin and Salomon, 2003).

We argue that suppliers' knowledge transfer capabilities are highly important in licensing situations for two reasons. First, this capability increases the likelihood that potential buyers will understand the value of the suppliers' technology. Potential buyers, mostly industry incumbents, may entirely overlook the true value of novel technology created externally. Incumbents are known to examine new technologies from the perspective of how they fit with their existing product lines and downstream capabilities (Christensen and Bower, 1996). Many incumbents are also found to create information filters that absorb only the information that appears valuable to their existing operations (Henderson and Clark, 1990). Thus, to help incumbents understand the value of a novel invention, suppliers must penetrate such information filters and be able to communicate how the invention can add value to their products or markets.

The second reason that knowledge transfer ability is important in licensing is that suppliers' knowledge transfer capabilities help buyers to lower their integration costs. Even if a buyer understands the value of the new technology, integrating a novel technology into a new context (e.g., the buyer's product lines) can be a daunting task. For instance, buyers may lack the ability to leverage the new technology within their existing operations and manufacturing contexts. In this case, the supplier's knowledge transfer capability is crucial. Inventors' knowledge of how to reproduce and adapt their inventions to different contexts can greatly facilitate integration (Arora, 1995). If effectively codified or communicated, inventors'

DOI: 10.1002/smj

experiences with failed experiments or know-how about the environments in which the technology works best will mitigate uncertainty and unnecessary trial and error for buyers. Thus, we assume that the seller's knowledge transfer capability lowers the expected integration costs to $D(1-\delta)$, with $0<\delta<1$.

Analysis

Figure 1 summarizes the payoff functions of the technology supplier and the potential buyer. Licensing will take place between the parties if their net gains from licensing exceed their net gains from competition. This amounts to the following condition:

$$\Delta \equiv \underbrace{(\tau^* - c) + [\pi^m - \tau^* - (1-\delta)D(k,\alpha) - c]}_{\text{parties' net gains from licensing}} - \underbrace{[\pi^c - A(k) + \pi^c - I]}_{\substack{\text{parties' net gains}\\ \text{from competition}}} > 0,$$

where τ^* is the equilibrium price that the potential buyer would pay for the technology, which cancels out in the equation above.[3] Thus the condition can be rewritten as:

$$\Delta = \pi^m - 2\pi^c - 2c + A(k) + I - (1-\delta)D(k,\alpha) > 0.$$

The likelihood of licensing increases with Δ, the net surplus from licensing. The net surplus is in turn a function of several parameters. Our focus is on the marginal effect of an increase in the supplier's knowledge transfer capability (δ) on the decision to license. In particular, we find that $\frac{\partial \Delta}{\partial \delta} = D(k,\alpha) > 0$. This positive effect follows from the intuition that the supplier's knowledge transfer capability facilitates the potential buyer's integration of the licensed technology, therefore increasing the net surplus from licensing for both parties and increasing the likelihood that licensing will take place between the parties.

Note that this result, however, cannot be *directly* tested because by definition a *potential* buyer is not always observable. To directly test the result one would need to identify each potential buyer, including any that have considered negotiating a license with the supplier but decided not to do so, and any that have negotiated with the supplier but failed to reach an agreement. These potential buyers are not always observable by econometricians. Nevertheless, our model implies a more testable hypothesis, which predicts licensing to *an industry* rather than licensing to a specific potential buyer. All else equal, a technology supplier that has a greater capability of transferring knowledge to an industry is more likely to attract licensees in this industry. Thus, we hypothesize the following.

> *Hypothesis 1: A technology supplier's knowledge transfer capability in an application industry increases the likelihood that the supplier will out-license its technologies to this industry.*

Our model also implies that the effect of the supplier's knowledge transfer capability is critically conditioned by the absorptive capacity (α) of the potential buyer in the application industry. In particular, results of comparative statics analysis indicate that the importance of a supplier's knowledge transfer capability for licensing decreases with the absorptive capacity of the potential buyer, that is, $\frac{\partial^2 \Delta}{\partial \delta \partial \alpha} = \frac{\partial D(k,\alpha)}{\partial \alpha} < 0$. This result is primarily driven by the negative sign of $\frac{\partial D(k,\alpha)}{\partial \alpha}$, which comes from our argument that integrating the supplier's technology is more challenging and costly for a potential buyer that has a lower α. As a result, the value of licensing will depend more on the supplier's knowledge transfer capability. Again, although this result is at the dyad level, it implies a testable hypothesis that predicts a supplier's licensing to a specific industry. All else equal, licensing to an industry is more challenging when the typical level of absorptive capacity of potential buyers is lower; thus successful licensing to such an industry is more likely to depend on the supplier's knowledge transfer capability.

> *Hypothesis 2: The importance of a technology supplier's knowledge transfer capability for licensing is higher for an application industry where the typical absorptive capacity of potential buyers in this industry is lower.*

[3] Interested readers can refer to our online appendix to see the derivation of this equilibrium price, determined by the Nash bargaining solution (Nash, 1950). This price allows us to compute the technology supplier's net gain from licensing and shows that the condition here ($\Delta > 0$) is equivalent to the condition for the technology supplier's net gain from licensing to exceed its net gain from vertical integration.

A second factor affecting the net surplus from licensing (Δ) is the nature of the interaction between upstream and downstream activities required to commercialize the technology. In particular, application industries that require cospecialization between R&D and downstream activities would have a relatively high cost of integrating the supplier's technology. In this case, the supplier's knowledge transfer capability would be especially helpful to lower the integration cost for buyers and thus facilitate licensing. Consistent with this intuition, our model indicates that the importance of a technology supplier's knowledge transfer capability for licensing increases with cospecialization, that is, $\frac{\partial^2 \Delta}{\partial \delta \partial k} = \frac{\partial D(k, \alpha)}{\partial k} > 0$.[4]

Hypothesis 3: The importance of a technology supplier's knowledge transfer capability for licensing is higher for an application industry where the downstream activities required for technology commercialization in this industry are more cospecialized with R&D.

EMPIRICAL MODEL

Model specification and estimation methods

Our empirical model can be derived by noting that the probability that a technology supplier i will license a technology j, at time t, in application industry k, is a function of the surplus from licensing versus not licensing: $\mathrm{Pr}_{\mathrm{jikt}}(\mathrm{Licensing}) = Pr(\Delta_{jikt} > 0)$. The net licensing surplus Δ_{jikt} is, in turn, a function of x, which includes the drivers of licensing that we focus on in this study as well as the variables suggested by prior literature. However, Δ_{jikt} is also driven by factors that are specific to the focal technology j, which is unobserved by researchers. We therefore assume that the net surplus from licensing incorporates an unobserved technology-specific random shock with zero-mean, ε_{jikt}, and that Δ_{jikt} has a form of $\beta x + \varepsilon_{jikt}$, with β being the coefficients to be estimated. As such, the expected probability of licensing can be rewritten as

$$\mathrm{Pr}_{\mathrm{ikt}}(\mathrm{Licensing}) = Pr(\Delta_{jikt} > 0) = F(\beta x), \quad (1)$$

with F being a symmetric cumulative distribution function for ε_{jikt}. In other words, under the assumptions above, the unobserved components of the gains from trade and the transaction cost at the technology level are conditioned out.

We can then derive the expected number of firm i's licensing agreements in the potential application industry k at time t (i.e., *Out-licensing*$_{ikt}$), as a function of the probability of licensing multiplied by the number of technologies that could potentially be licensed (T_{ikt}).

$$Out\text{-}licensing_{ikt} = F(\beta x) \times T_{ikt}. \quad (2)$$

Note that T_{ikt} is unobserved. However, we can observe the number of granted patents held by the technology supplier i in the application industry k during year t, as P_{ikt}. A granted patent represents a necessary condition for technology licensing in most cases, especially in the manufacturing sector (Arora and Ceccagnoli, 2006). Thus, T_{ikt} is proxied by P_{ikt}, the number of granted patents held by the supplier i at time t that can be potentially used for application industry k.

Since our dependent variable in Equation (2) is a nonnegative count, we use a Poisson model with standard errors adjusted for overdispersion. The expected value of our dependent variable can thus be specified as an exponential function of X, which is a vector that includes the number of patents P_{ikt} and other drivers of licensing x.

$$E(Out\text{-}licensing_{ikt}|\mathrm{X}) = exp(BX). \quad (3)$$

The coefficients (B) in Poisson models represent the percentage change in the expected count of the dependent variable for a unit change in the covariates. Since we use the natural log of our main independent variables, their coefficients can be interpreted as elasticities, thus providing information about the magnitude of the effects of interest.

We shall note that two important sources of unobserved heterogeneity may bias our estimates. One is the unobserved variation in the value of

[4] Note that our Hypotheses 2 and 3 assume the separability of δ and $D(\alpha, k)$. If the integration cost was $D(\delta, \alpha, k)$ instead $(1-\delta)D(k, \alpha)$, one would need to assume the cross partials of D with regard to α and δ, and with regard to k and δ to derive the same hypotheses. We believe that our simplified assumption of integration costs as $(1-\delta)D(k, \alpha)$ is reasonable because it captures the dynamics that the integration cost is reduced if the supplier has a positive knowledge transfer capability and that if the supplier has zero capability of facilitating knowledge transfer, the buyer incurs the full integration cost $D(\alpha, k)$.

DOI: 10.1002/smj

a supplier's technologies for an application industry. A second is the number of patents required per licensing deal, which can also vary across firms and application industries. Such unobserved variations, if not controlled for, can lead to estimation bias. To address this issue, we controlled for a firm-application industry 'fixed effect' (c_{ik}) by estimating Equation (3) using a pooled Poisson quasi-maximum likelihood model (QMLE) with a Chamberlain–Mundlak correlated random-effect device (Wooldridge, 2010). The Chamberlain–Mundlak method controls for panel-specific unobserved effects using the averages of all the explanatory variables across years within each panel (i.e., each firm i and its industry k). We further clustered standard errors by firms and their respective application industries. As a robustness check, we also estimated the conventional fixed-effects Poisson model, which conditions c_{ik} out prior to estimation.

Data and sample

To test our hypotheses, we constructed our sample and variables based on multiple data sources. The licensing agreements of our sample firms come from the Thomson Reuters SDC Platinum alliances database. From this database we also gathered longitudinal information on each firm's knowledge transfer capability. The small-firm patent database sponsored by the Office of Advocacy of the Small Business Administration (SBA) provided information about the patents of sample firms. We supplemented this data with the National Bureau of Economic Research and Thompson Delphion patent databases. Additionally, we collected sample firms' trademark data from the USPTO. Sample firms' potential application industries were based on the patent data mentioned above, as well as the 2005 USPTO patent-industry concordance. Measures of absorptive capacity and asset cospecialization in the potential application industries were obtained using the 1994 Carnegie Mellon Survey on industrial R&D, as summarized by Cohen, Nelson, and Walsh (2000). We also used Compustat to identify the potential market size and average R&D intensity in the potential application industry.

The SBA database, in particular, defines our sample. This database contains detailed patent information on the population of more than 1,200 private and public U.S. companies with at least 15 patents between 1998 and 2002.[5] These firms have been defined as the population of U.S. 'serial innovators,' or technology-based firms that were able to sustain innovation beyond the first great idea upon which the firms were founded (CHI-Research, 2003; Hicks and Hegde, 2005). The strength of the SBA database is that its identification of these companies unifies all the establishments and subsidiaries with their parent companies and counts their patents toward the overall parent patent count, which is a challenging task, especially for small private companies. From this database, we selected the small firms (those with fewer than 500 employees). Our final sample is based on an unbalanced panel of 519 firms with nonmissing observations for the variables of interest.

To test our hypotheses, an important task was to identify the application industries in which the patents of the sample firms could *potentially* be used. These application industries should include both the industries to which a sample firm successfully granted licenses and the industries that the sample firm could have considered but failed or chose not to grant a license. To identify these application industries for each sample firm, we exploited the concordance developed and maintained by the USPTO. The USPTO concordance links each patent class to one or more of the 56 industries/sectors (hereafter the 'sequence codes') that are expected to produce the product claimed in the patent or to use the new patented processes in the manufacturing of their products.[6] For each firm in our sample, we collected a list of sequence codes

[5] The threshold of 15 patents was necessary to ensure accurate firm identification for the population of inventive firms in the United States (Hicks, 2002). This is due to both the challenges of matching assignees to parents and the volatility among small firms, which are acquired or disappear regularly. In other words, substantial work must be carried out to ensure that the patentees were in business and independent. Ignoring this point would compromise the integrity of the results.

[6] Each of these sequence codes corresponds to one or more, two- to four-digit SICs (see http://www.uspto.gov/go/taf/brochure.htm, the table of the correspondence code is also available from the authors upon request). Paul Harrison from the USPTO (Paul.Harrison@uspto.gov) provided us with the decision rules used for the concordance: 1. Determine if patents in a U.S. Patent Classification System (USPCS) subclass are product, apparatus and/or process. 2. If product, determine type of establishment that would be engaged in producing that type of product. 3. If apparatus, determine type of establishment that would be engaged in producing that type of apparatus. 4. If process, determine whether process more closely related to the product of that process or apparatus used in the process, then classify accordingly. 5. If unable to determine, then place in all possible SIC categories.

corresponding to the primary technology class of its patents as potential application industries. We then built a panel dataset with repeated observations over time for each sample firm in each of its potential application industries. This allowed us to have our dependent variable and several independent variables vary by firm, sequence codes, and years, with the firm and sequence code pair representing the panel.

It is important to note that in using the sequence codes of a firm's patents to identify its potential application industries, our data are not limited to the industries where licensing was observed. This allowed us to predict licensing using the characteristics of all potential application industries without suffering from selection bias, which would occur if one predicted licensing using only the industries in which licensing actually occurs.

Main variables

Out-licensing$_{ikt}$. Our dependent variable is the number of times the focal firm i licenses to a buyer in an application industry k in year t during our study period (1996–2007). The data comes from the SDC Platinum alliances database available from Thomson Reuters. We first identified the technology-based licensing agreements of our sample firms and used the deal description in SDC to select only those in which the sample firms were the technology suppliers. In the few cases where the deal description did not specify which firm was the supplier, we complemented our search with data from online archival news sources. In a second step, we used the above information to determine which application industry the licensing was targeting, using both the SIC industry code of the alliance assigned by SDC and the analysis of the synopsis.

As a result of these efforts, we found that each sample firm granted from zero to eight licenses each year to each of its application industries. A summary of the statistics and correlations for this variable (as well as the remaining variables detailed below) is presented in Table 1a.

Codevelopment experience$_{ikt}$. Teece (1997) suggests that a firm gains knowledge transfer capability from its experiences over time.[7] We thus measure a firm's knowledge transfer capability based on the firm's experiences in transferring knowledge across firms. An important channel of such knowledge transfer is codevelopment, such as R&D alliances, which involve information sharing, technical assistance, and trust and reputation building between firms. A firm's rich experience in these activities is likely to be associated with a stronger ability to coordinate and communicate with partners (Schreiner, Kale, and Corsten, 2009), and thus a stronger knowledge transfer capability. Thus, we measured a firm i's knowledge transfer capability in year t as the cumulative number of codevelopment deals in which firm i's technologies were used to develop applications for industry k.[8] We identified these deals from the SDC database by reading each deal synopsis and selecting those deals that involved the transfer of a focal firm's knowledge. We depreciated the stock using a 15 percent discount rate, but also used the simple cumulative count as a robustness check.

Industry absorptive capacity$_k$. Hypothesis 2 suggests that the importance of a supplier's knowledge

[7] Teece (1977) suggests that the cost of technology transfer is reduced when the technology holder has accumulated experience in transferring technology in the past. For example, his findings suggest that a technology that had been transferred twice to another firm in the chemicals and petroleum refining sector incurred a technology transfer cost that was 34 percent lower than the cost to transfer the technology the first time around, *ceteris paribus*. The corresponding reductions in the technology transfer costs for the second and third projects in the machinery industry were 14 percent and eight percent, respectively. Such lower costs imply that the technology transferor gains efficiency at transferring knowledge over time—thus supporting our claim that the stock of the technology supplier's codevelopment alliances proxies for its knowledge transfer capability. While the cited evidence provides indirect support for our measure, our measure is not ideal. In principle, we would want to identify the knowledge transfer capability using each firm's organizational routines and structure for knowledge transfer and then measure the efficiency of these activities. Such data are, however, largely unobservable.

[8] An example of such codevelopment deals involves an electronic ink technology popular in today's consumer electronic mobile devices (the Kindle) introduced by E Ink, a company founded in 1997. In the early 2000s, E Ink partnered with Toppan Printing, Ltd. and Royal Philips Electronics to codevelop E ink's technology for use with high resolution color displays that can be used in mobile display applications. Since the E Ink technology was different from the existing display solutions, this codevelopment required E Ink to transfer its expertise about its cutting-edge technology to both partners and provide technical assistance. As Mr. Tsuyoshi Matsuo, head of Technical Research Institute at TOPPAN, said, 'This color development prototype represents an exciting step in TOPPAN's development of a technology platform for electronic paper devices with E Ink... we remain enthusiastic and committed to working with E Ink to develop these next generation displays' (E Ink, 2002).

DOI: 10.1002/smj

Table 1a. Summary statistics

	1	2	3	4	5	6	7	8	9	10	11	12
1. Out-licensing$_{ikt}$												
2. Codevelopment experience$_{ikt}$	0.30											
3. Industry absorptive capacity$_{k}$	0.08	0.16										
4. Industry asset cospecialization$_{k}$	−0.06	−0.12	−0.21									
5. Patents$_{ikt}$	0.15	0.18	0.11	−0.09								
6. References to science$_{ikt}$	0.08	0.21	0.11	−0.19	0.28							
7. Trademarks$_{ikt}$	0.00	0.02	−0.02	0.00	0.14	0.03						
8. Public$_{it}$	0.07	0.14	0.16	−0.14	0.16	0.29	0.00					
9. Firm age$_{it}$	−0.03	−0.05	−0.10	0.05	−0.04	−0.15	−0.03	−0.15				
10. Exit$_{it}$	−0.01	−0.01	0.03	−0.04	0.03	−0.03	−0.01	−0.02	0.04			
11. Industry capital intensity$_{kt}$	0.00	0.00	−0.21	−0.09	0.06	0.32	−0.06	0.19	−0.06	0.24		
12. Industry sales$_{kt}$	0.06	0.13	0.31	−0.27	0.17	0.07	0.03	0.13	−0.06	0.01	−0.18	
Mean	0.01	0.07	0.13	0.45	12	0.13	0.33	0.42	22.73	0.06	80.91	217,949
Standard deviation	0.14	0.41	0.02	0.08	18	0.24	1.59	0.49	22.80	0	73.67	236,513
Min	0	0	0.07	0.17	0	0	0	0	0	0	20.64	430
Max	8	14	0	0.76	456	1	49.04	1	147	1	458.46	2,970,184

[1] Our dataset comprises a total of 1,178 "potential" firm-application industries (FAIs) belonging to 519 firms and observed over an average of 10.9 years during the 1996-2007 period, for a total of 12,845 observations.
[2] All US dollars are in millions and in real terms deflated by the corresponding year's GDP deflator with the base year in 2005.

Table 1b. The changes of licensing with the changes of codevelopment experience averaged across the firm-application industry groups (FAIs)

	Likelihood of observing at least one out-licensing deal					Average cumulated number of out-licensing deals				
	First observation in the sample		*Last observation in the sample*		*Difference between last and first observation*	*First observation in the sample*		*Last observation in the sample*		*Difference between last and first observation*
	(1) Mean	(2) St.dev.	(3) Mean	(4) St.dev.	(5) (3)-(1)	(6) Mean	(7) St.dev.	(8) Mean	(9) St.dev.	(10) (8)-(6)
FAIs characterized by *constant* codevelopment experience during the sample period (N = 1, 121)	0.019	*(0.136)*	0.047	*(0.212)*	0.029***	0.021	*(0.154)*	0.079	*(0.493)*	0.059***
FAIs characterized by an *increase* in codevelopment experience during the sample period^ (N = 57)	0.035	*(0.186)*	0.228	*(0.423)*	0.193***	0.158	*(1.066)*	0.825	*(2.543)*	0.667**
All FAIs (N = 1, 178)	0.020	*(0.138)*	0.056	*(0.230)*	0.037***	0.027	*(0.278)*	0.115	*(0.751)*	0.088***

*** significant at 0.01; ** significant at 0.05.
Columns (5) and (10) report the significance of a two-sample t-test with equal variances of the null hypothesis that the difference between the means of the last and the first observations is greater than zero.
^: The average stock of codevelopment alliances for this group is zero at the beginning of the sample, and 0.842 at the end of the sample, with the difference in means significant at the .001 level.

DOI: 10.1002/smj

transfer capability varies with the typical absorptive capacity of the potential buyers in an application industry. We included the interaction of these two variables to empirically test this hypothesis.

To measure the absorptive capacity of potential buyers, an important step is to identify the set of these buyers. As mentioned, it is difficult to identify potential buyers because we only observe the actual buyers once the licensing takes place. Using only the characteristics of the actual partners to predict licensing would generate biased results. Our solution is that we identified all public firms in an application industry as the set of potential buyers from this industry. Public firms are typically incumbents that have relevant resources to commercialize products and for which data are available. We then measured the typical level of absorptive capacity of potential buyers from an application industry using the average absorptive capacity of these public firms. As such, variations across potential buyers mainly come from the variations across application industries. Although this method does not allow us to capture the full variation across potential buyers, it underestimates the effect of absorptive capacity and provides a conservative test.

We measured absorptive capacity from the Carnegie Mellon survey (CMS) on industrial R&D, which contains a measure of the percentage of R&D effort devoted to gaining novel external knowledge from a sample of 1,477 R&D labs that came from a broad range of industries.[9] Each lab was assigned a primary SIC code (which indicated the principal industry for which the lab was conducting its R&D). This allowed us to match the industry averages of the CMS absorptive capacity measure to each application industry using the USPTO concordance. Since this survey-based measure is time invariant, its main effect is not estimated in the conditional fixed-effect models. Nevertheless, for these models we can estimate the coefficient of the interaction term *codevelopment experience X industry absorptive capacity* because the value of the interaction term varies over time.

As a robustness check, we used each application industry's yearly *R&D intensity* (weighted by sales) as an alternative measure. This is a widely used measure of absorptive capacity since R&D investment increases absorptive capacity to exploit external knowledge flows (Cohen and Levinthal, 1989). The advantage of this measure for our study is that it varies across both time and application industries. But, we can only compute this measure for public firms because private firms do not disclose their R&D expenditure. Nevertheless, the potential buyers in our theory are industry incumbents with downstream capabilities, which indeed are very likely to be large public firms. Another limitation of this measure is that R&D investments also reflect internal R&D productivity, which suggests that R&D intensity is most likely a noisy measure of absorptive capacity.

Industry asset cospecialization$_k$. To measure cospecialization we used data from the CMS to compute the share of respondents (among the 1,477 R&D labs of the survey) whose R&D and marketing/manufacturing personnel interacted *daily*, per each application industry k. The possible responses include daily, weekly, monthly, rarely, and never. The median frequency reported by these labs was weekly. We adopted this measure based on the idea that when innovation and downstream assets are cospecialized, frequent and ongoing mutual adjustments between the two are necessary for commercialization (Kline and Rosenberg, 1986; Teece, 1992). In other words, our measure reflects the degree of bilateral dependence between upstream and downstream activities in the value chain (Teece, 1986). Note that although this measure is not time variant (the CMS was conducted in 1994), the level of complementarity among activities of commercializing innovations has been shown to change only moderately over time (Ceccagnoli and Rothaermel, 2008; Cohen *et al.*, 2000). To test Hypothesis 3, we interacted this measure with the focal firm's codevelopment experience measure.

Control variables

Patents$_{ikt}$. We controlled for the stock of technologies available for commercialization, or P_{ikt} in Equation (3). The measure is firm i's stock of U.S. patents as of year t that are potentially useful for industry k. We depreciated the stock of patents with a discount rate of 15 percent.

[9] The survey asked the following question: 'Approximately what percent of your R&D personnel's time is devoted to monitoring and gathering information on new scientific and technical developments?'.

DOI: 10.1002/smj

References to science$_{ikt}$. Licensing can also be a function of the codifiability of the technology, because transactions that involve codified information are generally less costly than those involving tacit information (Arora, 1995; Teece, 1977; von Hippel, 1994). From this perspective, codifiability can facilitate licensing. On the other hand, a more codified technology can increase the risk of negotiating a license. Such a technology, once disclosed to potential buyers, may be relatively easy for them to replicate and invent around (Teece, 1986). We control for these possible effects of technology codifiability using a common proxy based on patents' backward references to scientific publications. Specifically, the measure is computed as the percentage of science references among all the references made by firm i's patents that were granted in year t and applicable for industry k.

Trademarks$_{ikt}$. We controlled for a firm's complementary assets using its stock of trademarks. According to the USPTO (http://www.uspto.gov/trademarks/index.jsp[23 August 2012]), a trademark identifies and distinguishes the source of the goods or services of one party from those of others. Firms invest in trademarks as an important complementary asset to protect products, technologies, brands, and/or reputation (Fosfuri and Giarratana, 2009; Fosfuri, Giarratana, and Luzzi, 2008). Trademarks can also be thought of as complementary assets to promote sales of products or technologies. In prior studies, trademarks have also been used as a measure of marketing capabilities (Fosfuri *et al.*, 2008) and found to be correlated with another measure of marketing capability—the number of sales executives (Arora and Nandkumar, 2012). Thus, we collected trademark data from the USPTO CASSIS Trademarks BIB database, and computed the cumulative number of trademarks registered to firm i during year t and in application industry k, depreciated using a discount rate of 15 percent.[10]

Other firm characteristics. We controlled for whether a sample firm is publicly traded or privately owned ($public_{it}$) during our study period. Since public firms are more likely to announce their licensing deals promptly, we may be more likely to observe licensing deals by public rather than private firms. We also controlled for the age of a firm in year t (*firm age$_{it}$*), because as a firm becomes older, it may build up more downstream resources and rely less on licensing as a commercialization strategy. Finally, a dummy variable ($exit_{it}$) indicates whether firm i dropped out of our sample during the study period due to bankruptcy or mergers and acquisitions in year t. We obtained this information for private and public firms using Corptech and Compustat, respectively.

Sales-weighted size and capital intensity of application industries. Bresnahan and Gambardella (1998) show that the division of labor in markets for technology can be driven by the number of potential buyers and their product market sizes. To control for these effects, we included total sales of public firms in application industry k during year t (*industry sales$_{kt}$*). We also controlled for the capital intensity of application industry k during year t (*industry capital intensity$_{kt}$*). Capital intensity is the value of property, plant, and equipment in millions per thousand employees. All these data were obtained from Compustat. The data in dollars were converted into real terms using the corresponding year's U.S. GDP deflator, with 2005 as the base year.

Firm-industry fixed effect and year dummies. As mentioned above, we controlled for the unobserved heterogeneity that is time invariant and specific to each firm and application using the time averages of all the explanatory variables. We also included year dummies to control for time-varying unobserved effects on firms' licensing (η_t) during the 1996–2007 period.

[10] Since trademarks are classified by product classes, they can be easily matched to application industries. Specifically, goods and services protected by trademarks are classified into 42 international classes, most of which can be linked to two-digit SIC and industry sequence codes (http://www.uspto.gov/faq/trademarks.jsp#Application018). For the classes that can be assigned to multiple industries, we used a 'fractional count' method analogous to the way the USPTO counts patents by SIC (http://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_pat_tr.htm#PATR_) for their 'Patenting Trends in the United States' reports, wherein a patent class can be assigned to multiple SICs. For example, since trademark class 11, 'Environmental control apparatus,' can be assigned to sequence codes 38 and 55 ('Electrical lighting and wiring equipment' and 'Professional and scientific instruments'), we assigned 50 percent of class 11 trademarks to each of the two sequence codes. The full concordance is available from the authors upon request.

DOI: 10.1002/smj

RESULTS

Before presenting our benchmark results, we present some descriptive evidence for the relationship between licensing and knowledge transfer capability suggested in Hypothesis 1. Columns 1–5 of Table 1b show the likelihood of observing at least one out-licensing deal for each firm and its application industry (FAI) at the time of entry and exit from the sample, averaged within two groups of FAIs. One group includes the FAIs characterized by an increase in codevelopment experience during the sample period; the other includes the FAIs that did not have such an increase. As shown in Column 5, among the 1,121 FAIs whose codevelopment experience did not increase, the likelihood of observing at least one out-licensing deal increased by 2.9 percent over the study period. Those 57 FAIs that were characterized by an increase in their codevelopment experience saw a 19.3 percent increase. Columns 6–10 show a similar pattern in the average cumulative number of out-licensing deals: it increases by 0.059 for the FAIs that presented no change in their codevelopment experience, while it increases by 0.667 for those FAIs that are characterized by an increase in their codevelopment experience. All these temporal changes are significant to at least the 0.05 level. Overall, our data suggest that variation over time in licensing of the focal firms within its application industry is positively and significantly correlated to variation in these firms' knowledge transfer capability, providing preliminary support for Hypothesis 1. This correlation also shows a source of variation in our data that underlies the empirical identification for our subsequent regression analyses.

Benchmark results

Table 2 shows the estimates of the pooled Poisson QMLE model with unobserved heterogeneity. In Model 1, we included our main independent variable of interest along with all the controls to test Hypothesis 1. The effect of *codevelopment experience* on licensing is positive and significant at the 0.05 significance level. The magnitude of the coefficient represents a standard elasticity, which indicates that a one percent increase in a firm's codevelopment experience would yield a 0.8 percent increase in the firm's out-licensing, thus supporting Hypothesis 1.

To test Hypothesis 2, we introduced the interaction of *codevelopment experience* with *industry absorptive capacity* in Model 2 of Table 2. Consistent with expectations, the estimated coefficient is negative and significant. To test Hypothesis 3, we introduced the interaction of *codevelopment experience* with *industry asset cospecialization* in Model 3. The coefficient of this interaction term is positive and statistically significant at the 0.05 significance level, as expected in Hypothesis 3. Note that the high correlation (>0.9) between the two interaction terms precludes us from estimating their separate effects in the same regression. This high correlation is caused by the fact that the two interaction terms share a common variable and each includes a time-invariant variable.

To examine the interaction effects in more detail, in Table 3 we present the marginal effects of *codevelopment experience* at different levels of *industry absorptive capacity* and *industry cospecialization*. While on average a one percent increase in a firm's codevelopment experience yields a 4.2 percent ($p < 0.01$) increase in the firm's out-licensing activity, the elasticity drops to 1.4 percent ($p < 0.01$) when *industry absorptive capacity* is one standard deviation above its mean (Column 2). The change in the elasticities is statistically significant ($p < 0.01$). Thus, as predicted in Hypothesis 2, the importance of a firm's knowledge transfer capability is reduced when the potential buyers' absorptive capacity is higher.

We also find support for Hypothesis 3, according to which the importance of a firm's knowledge transfer capability increases when R&D and downstream activities are cospecialized. The third column of Table 3 shows that while a one percent increase in a firm's codevelopment experience on average yields a 3.7 percent ($p < 0.01$) increase in licensing, the elasticity increases to 6.7 percent ($p < 0.01$) when *industry asset cospecialization* is one standard deviation above its mean. This change in the elasticities is significant at the one percent significance level.

Among our control variables, *references to science* has a negative effect on out-licensing. While it is hard to interpret this effect due to the contamination of the industry fixed effects, this result seems to suggest that in our sample, the fear of disclosing codified technology dominates the lower cost of transferring such technology. Another possible explanation is that this variable may capture a third effect: the stronger

DOI: 10.1002/smj

Table 2. Benchmark models: pooled Poisson estimation

Dependent variable: Number of out-licensing deals	Model 1	Model 2	Model 3
Codevelopment experience$_{ikt}$	0.82**	−25.90***	−16.09***
	(0.39)	*(8.04)*	*(5.69)*
Industry absorptive capacity$_{k}$	1.82**	1.90**	1.81**
	(1.01)	*(1.11)*	*(1.04)*
Industry asset cospecialization$_{k}$	−0.51	−0.24	−0.93
	(3.88)	*(3.91)*	*(3.90)*
Patents$_{ikt}$	0.26*	0.26*	0.25*
	(0.20)	*(0.20)*	*(0.19)*
References to Science$_{ikt}$	−0.97**	−0.90*	−0.89*
	(0.56)	*(0.57)*	*(0.57)*
Trademarks$_{ikt}$	−0.59*	−0.61**	−0.61**
	(0.36)	*(0.36)*	*(0.36)*
Public$_{it}$	0.56*	0.54*	0.52*
	(0.41)	*(0.41)*	*(0.41)*
Firm age$_{it}$	1.93***	1.90***	1.88***
	(0.78)	*(0.79)*	*(0.79)*
Exit$_{it}$	−0.84*	−0.84*	−0.84*
	(0.60)	*(0.60)*	*(0.60)*
Industry sales$_{kt}$	0.91	0.93	0.93*
	(0.73)	*(0.73)*	*(0.73)*
Industry capital intensity$_{kt}$	−0.51	−0.70	−0.72
	(*1*.00)	(*1*.00)	(*1*.00)
Constant	−11.63***	−11.72***	−11.77***
	(4.61)	*(4.60)*	*(4.53)*
Codevelopment experience$_{ikt}$ X industry absorptive capacity$_{k}$		−14.53*** *(4.33)*	
Codevelopment experience$_{ikt}$ X industry asset cospecialization$_{k}$			53.50*** *(17.86)*
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)	(Yes)	(Yes)
Number of obs.	12,845	12,845	12,845
Log likelihood	−459.58	−457.75	−457.79

Number of firm-industry groups = 1178.
Robust standard errors clustered at the firm-application industry level in parentheses.
*** significant at 0.01; ** significant at 0.05; * significant at 0.1.
†: Controlled for by including the time averages of the time-varying explanatory variables.

Table 3. Effects of codevelopment experience at different levels of the moderating variables z (from Table 2)

	z=Industry absorptive capacity	z=Industry asset cospecialization
When z is at its mean	4.21***	3.74***
	(1.02)	*(1.01)*
When z is one standard deviation above its mean	1.37***	6.67***
	(0.38)	*(1.95)*
Changes in the marginal effect	−2.84***	2.93***
	(0.85)	*(0.98)*

The table shows the percent change in the number of licensing deals for one percent change in the *codevelopment experience.*
*** significant at 0.01.

the scientific nature of the knowledge underlying the technology, the more basic the technology might be, and such technology may find relatively fewer opportunities to be used commercially. Moreover, a firm that produces more science-based technology might also face more

DOI: 10.1002/smj

competition from university licensors, which could reduce opportunities to license.

Robustness

We performed various robustness checks to validate our findings. The results of these alternative regressions are shown in Appendix Tables A1, A2, and A3. First, we show the results of logit models to emphasize that our empirical testing is not conditional on the observation of actual licensing and to provide additional evidence of the marginal effects of the variables on the probability of licensing. In the logit models, the dependent variable takes a value of 1 if an actual licensing by firm i to industry k took place in year t and 0 otherwise. The results, shown in Models 1 and 2 of Table A1, are consistent with our benchmark results. Specifically, a one percent increase in a firm's *codevelopment experience* yields a slightly over three percent increase in the probability of licensing at the mean of the sample. This effect drops to 1.5 percent when *industry absorptive capacity* is one standard deviation above the mean, while it increases to 5.5 percent when *industry asset cospecialization* is one standard deviation above the mean. These changes are significant at the 0.05 significance level.

Second, as previously mentioned, we ran a Poisson regression model with conditional fixed effects as an alternative way to control for the unobserved effects specific to each group (i.e., firm i and its application industry k). Because the group-specific effects are conditioned out prior to parameter estimation, it does not estimate the coefficients of time-invariant variables, including the main effects of *industry absorptive capacity* and *industry asset cospecialization*. Nevertheless, we could still estimate the coefficient of the interaction of these variables with a firm's knowledge transfer capability, because the latter is time variant. The results are consistent with our main results. The reduction in the marginal effect of *codevelopment experience* with the increase of *absorptive capacity* is statistically significant at the 0.05 level (Model 3 of Table A1), whereas the increase in the marginal effect with the increase of *industry asset cospecialization* is marginally statistically significant at the 0.1 level (Model 4 of Table A1).

Additional robustness checks include using alternative measures and splitting samples. First, we used alternative specifications of the discount rate for *codevelopment experience*—zero and 20 percent (the benchmark model used a discount rate of 15 percent). We reported the results using the zero discount rate in Models 1–3 of Table A2. The results of using 20 percent discount rate are very similar, and thus are not reported here. Second, we measured the expected absorptive capacity of potential buyers in an application industry using an alternative measure that varies over time and industries—the application industries' average $R\&D\ intensity_{ikt}$ (Models 4–6 of Table A2). Third, Models 7–9 of Table A2 show the results when data is limited to the primary application industry of each firm (the industry for which a firm had the most patents during the sample period), to check whether the estimates are influenced by the number of potential application industries considered. The results from the above robustness checks are consistent with our main predictions. Furthermore, Table A3 shows our benchmark model estimated on the split samples. Specifically, to test Hypotheses 2 and 3, we split our sample into two subsamples based on whether the value of *industry absorptive capacity* and *industry asset cospecialization*, respectively, is greater or smaller than the sample medians. Consistent with Hypotheses 2 and 3, we found that the effect of *codevelopment experience* is greater when *industry absorptive capacity* is smaller or when *industry asset cospecialization* is higher.

Further robustness checks, available from authors upon request, are not shown here because of space limitation. First, although we controlled for the value of the suppliers' technologies by firm-industry fixed effects and, to some extent, by the variable $Patents_{ikt}$, we have considered other possible measures. A common measure is the patents weighted by the number of forward citations. However, some forward citations may come from the licensees as a result of licensing. Thus instead of using forward citations, we used two other variables to control for the value of the suppliers' technologies: the number of backward patent citations and the number of claims of firm i's patented technology in year t and application industry k. Both variables have been used to measure patent quality (Lanjouw and Schankerman, 2004). Our main results are robust to the inclusion of these additional controls. In another robustness test, we controlled for the application industries' overall technical capability to take into account the buyers' internal development capability using the industry

DOI: 10.1002/smj

average *R&D intensity*$_{ikt}$. Our main results remain qualitatively unchanged.

As a final note, we would like to point out that although we are controlling for time-invariant unobserved firm heterogeneity, the estimated effect of a firm's knowledge transfer capability on licensing could still suffer from omitted variable bias due to time-*varying* unobserved heterogeneity. In particular, to the extent that firms can invest in knowledge transfer capabilities over time, it is possible that incentives to do so are higher when technology transfer is difficult and, therefore, when licensing is less common. As a result, it is possible that some unobserved factors that are negatively correlated with the licensing activity of a focal firm are positively correlated with its codevelopment capabilities. Given this possibility, the effect of knowledge transfer capabilities on licensing would tend to be characterized by a downward bias. This suggests that the results presented in this paper provide a lower bound for the impact of knowledge transfer capabilities on licensing.

DISCUSSION AND CONCLUSION

In this study, we investigated the factors that drive or limit the use of markets for technology through arm's-length transactions (such as licensing). In particular, we contribute to prior literature by highlighting an important hurdle of technology transactions: the potential buyers' costs of integrating external technologies into their specific product market. We view licensing as a bargaining problem in which both the inventing firm and a potential buyer consider the costs of technology integration along with other known factors (such as transaction costs, entry costs, and appropriability) when determining whether to enter into a licensing agreement. Examining the need for buyers to adapt and integrate an external technology allows us to understand licensing more fully from the perspectives of the demand side of the market.

This study also highlights the importance of firm capabilities in determining the use of markets for technology, particularly the supplier's ability to transfer knowledge and the potential buyer's ability to absorb knowledge. We first argue that the supplier's capability to transfer knowledge to a target industry is critical to offset the costs of integrating the external technology within the potential buyers' value chain. Consistent with this argument, our findings show that potential buyers in an industry are more likely to adopt and license technology from a supplier that has higher knowledge transfer capability. Second, we argue that the cost of integrating the technology into an industry's applications is lowered by the potential buyers' absorptive capacity. In support of this we found that for industries in which potential buyers typically have a higher absorptive capacity, licensing is less likely to depend on the supplier's knowledge transfer capability. This result parallels the markets for technology literature's finding that international technology transfers benefit from bundling patent licensing with the transfer of know-how, especially when the buyer is located in a less developed country (presumably with weak absorptive capacity) (Arora, 1996).

A shift in focus to technology integration costs and firm capabilities also allows us to contribute to a deeper understanding of the role of cospecialization between R&D and downstream assets. Teece (1986) and Gans *et al*. (2002) suggest that higher cospecialization between a new technology to be commercialized and the complementary assets necessary to enter a product market, *ceteris paribus*, increases the small firm's cost of entering the market and thus its incentives to out-license. We extend their work by suggesting that this prediction does not hold when the small firm has weak knowledge transfer capabilities. The intuition driving our finding is that because higher cospecialization is associated with bilateral dependence between R&D and downstream activities, conducting these activities in two separate organizations leads to an increase in the costs of integrating the external technology into the buyer's value chain. Consequently, unless the supplier is very skillful in knowledge transfer, a higher cospecialization may reduce buyers' incentive to license. Consistent with this idea, we find that the supplier's knowledge transfer capabilities are more important when commercialization involves higher cospecialization between R&D and downstream assets.

Taken together, our findings contribute to a deeper understanding of the role of capabilities in firms' boundary choices, a topic that has recently received increasing emphasis (Ceccagnoli *et al*., 2010; Leiblein and Miller, 2003; Parmigiani and Mitchell, 2009; Qian, Agarwal, and Hoetker, 2010). Our study is also consistent with recent contributions to the knowledge-based theory of governance choice, according to which the governance

DOI: 10.1002/smj

forms of transactions should overcome hazards or difficulties in knowledge recombination (Nickerson and Zenger, 2004). When buyers can easily recombine knowledge from the supplier, pure market transactions such as licensing are sufficient to generate value. However, when buyers have difficulty combining knowledge from sellers (either due to a low absorptive capacity or high cospecialization between R&D and downstream activities), a market transaction is not a sufficient form of governance to solve the problem. The buyers will need technical assistance, thus requiring suppliers that are experienced in knowledge transfer in order to facilitate knowledge recombination and value creation.

We also point out some of the limitations of our study. First, our analysis does not account for the possibility that small, technology-based firms have alternative cooperative commercialization strategies at their disposal, such as selling out the company to incumbents or forming a joint venture. We believe that expanding the choice set is an important and relatively unexplored line of research in the markets for technology literature, especially in the interest of understanding the optimal mode of cooperation in technology commercialization. Second, this study does not empirically predict licensing between a supplier-buyer dyad because we do not have firm-level data for all *potential* buyers including those that have not approached the sample firm for licensing. For this reason, we have carefully characterized our study's findings as supporting how the importance of licensors' knowledge transfer capability on licensing is conditioned by key features that characterize the potential application industries. We leave the supplier-buyer-level study as a challenging but promising future research opportunity. The third limitation is that we are unable to completely separate the two hypothesized conditioning effects when both are estimated in the same regression model. As we have discussed earlier, this is caused by the high correlation between the two interaction terms, which is in turn caused by the time-invariant, demand-side measures that enter these interaction terms. A better, time-variant measure of the demand-side variables is thus warranted for future research. Finally, Schilling's (2009) recent investigation of the database commonly used for alliance research suggests these databases, including SDC, do not report the population of all deals and is subject to a bias toward alliances formed between public large firms. Thus it is likely that our study undercounts deals for firms that are not publicly traded. Nevertheless, SDC still provides the most coverage for a representative sample like ours that is across various industries (Schilling, 2009). We attempted to limit the impact of the possible bias by controlling for whether a firm was public and the firm-application industry fixed effects.

Overall, our study provides practical guidance for small firms with a sustained record of inventions but limited downstream capabilities. In particular, our study suggests that managers of these firms should pay close attention to their potential buyers' ability to integrate external technologies: when such ability is low, licensing would be less likely to be successful without a strong knowledge transfer or technical assistance capability on the part of the supplier. Additionally, managers of the suppliers should also be aware of how interdependent the value chain activities of the potential buyers are: tighter and more frequent communication or coordination between R&D and marketing and manufacturing activities would also demand a greater knowledge transfer capability on the part of the suppliers. Meanwhile, our study suggests that firms that are buying external technologies should look for suppliers with a strong knowledge transfer capability and such capability can be identifiable from their past codevelopment alliances. In light of today's frequent demand for know-how transfer in licensing, suppliers that are able to accomplish this transfer efficiently will add critical value to their buyers.

In conclusion, this study focuses on a critical but overlooked bottleneck in licensing—the potential buyers' cost of integrating external technologies. By identifying the key supply- and demand-side factors that help overcome such costs, we provide insights on how to create value in the markets for technology and thus help the economic performance of both buyers and suppliers.

ACKNOWLEDGEMENTS

The authors contributed equally to this work. We thank Editor Will Mitchell, the anonymous reviewers, Ashish Arora, Janet Bercovitz, Annamaria Conti, Erika Damsgaard, Chris Forman, Alfonso Gambardella, Marco Giarratana, Matt Higgins, Jay Lee, Jackson Nickerson, Alex Oettl, Henry Sauermann, Grid Thoma, Marie and Jerry Thursby, and conference participants at the 2010 Atlanta Competitive Advantage Conference, the 2011 Wharton Technology Conference, and the 2011 Darden Entrepreneurship and Innovation Research Conference for their helpful comments. Ceccagnoli thanks the Ewing Marion Kauffman Foundation for its financial support. Jiang acknowledges funding from the National Nanotechnology Infrastructure Network (Sub-award 44771-7471 and NSF Award 0335765) and the Mildred and Alan Peterson Foundation. We also thank Diana Hicks and the Office of Advocacy of the Small Business Administration for sharing their data, as well as Wesley Cohen for sharing the Carnegie Mellon survey data. We thank Hyun Jung and Khosla Kunal for excellent research assistance.

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APPENDIX

Table A1. Robustness analyses with alternative estimation methods

Dependent variable	Model 1	Model 2	Model 3	Model 4
	Pooled logit		Poisson fixed-effects	
	Dummy = 1 if at least one out-licensing deal		Number of out-licensing deals	
Codevelopment experience$_{ikt}$	−20.62**	−11.87*	−17.84**	−7.93
	(10.32)	*(7.30)*	*(10.34)*	*(6.83)*
Industry absorptive capacity$_{k}$	1.50*	1.55*		
	(1.12)	*(1.06)*	.	.
Industry asset cospecialization$_{k}$	−0.42	−0.58	.	.
	(3.57)	*(3.58)*	.	.
Patents$_{ikt}$	0.29*	0.28	0.32	0.32
	(0.22)	*(0.22)*	*(0.29)*	*(0.29)*
References to science$_{ikt}$	−1.01*	−1.00*	−0.64	−0.65
	(0.64)	*(0.64)*	*(0.59)*	*(0.59)*
Trademarks$_{ikt}$	−0.84**	−0.85**	−0.64**	−0.66**
	(0.43)	*(0.43)*	*(0.33)*	*(0.33)*
Public$_{it}$	0.51	0.49	.	.
	(0.52)	*(0.52)*		
Firm age$_{it}$	1.36**	1.36**	3.19**	3.17**
	(0.74)	*(0.74)*	*(1.48)*	*(1.47)*
Exit$_{it}$	−0.82	−0.82	−0.63	−0.63
	(0.67)	*(0.66)*	*(0.66)*	*(0.66)*
Industry sales$_{kt}$	0.92	0.94	0.89	0.85
	(0.73)	*(0.73)*	*(1.71)*	*(1.71)*
Industry capital intensity$_{kt}$	−1.53*	−1.52*	−1.66	−1.68
	(1.01)	*(1.01)*	*(2.13)*	*(2.18)*
Constant	−10.44**	−10.40**		
	(4.69)	*(4.64)*		
Codevelopment experience$_{ikt}$ X industry absorptive capacity$_{k}$	−12.07** *(5.49)*		−10.14** *(5.58)*	
Codevelopment experience$_{ikt}$ X industry asset cospecialization$_{k}$		42.55** *(22.45)*		27.62* *(21.42)*
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)†	(Yes)†	(Yes)	(Yes)
Marginal effects of a 1% increase *codevelopment experience*$_{ikt}$				
i. at the mean of the sample	0.033***	0.031***	1.57***	1.43***
	(0.011)	*(0.011)*	*(0.52)*	*(0.58)*
ii. with *industry absorptive capacity$_{k}$* at one standard deviation above mean	0.015*** *(0.004)*		0.28 *(0.51)*	
iii. with *industry asset cospecialization$_{k}$* at one standard deviation above mean		0.055*** *(0.022)*		2.31** *(1.18)*
Number of obs.	12,845	12,845	723	723
Log pseudolikelihood	−377.74	−378.08	−205.34	−205.61

*** significant at 0.01; ** significant at 0.05; * significant at 0.1.
†: Controlled for by including the time averages of the time varying explanatory variables.
"." means the corresponding variable was dropped from estimation because of collinearity or lack of variation. In particular, in the fixed-effects models (Models 3-4), the variables that do not vary by time are conditioned out prior to parameter estimation.

Table A2. Robustness analyses with alternative measures and samples (pooled Poisson estimation)

Dependent variable: Number of out-licensing deals	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	(Discount factor = 0 for *codevelopment experience*)			(Replace industry absorptive capacity with *R&D intensity*)			(Sample including only the primary application industry for each firm)		
Codevelopment experience$_{ikt}$	0.76**	−15.83*	−9.88*	0.79**	2.81**	−11.91**	0.79**	−26.50***	−13.37**
	(0.39)	*(10.22)*	*(6.51)*	*(0.40)*	*(1.55)*	*(5.23)*	*(0.43)*	*(9.41)*	*(5.94)*
Industry absorptive capacity$_k$	1.75**	1.65**	1.79**	3.83	9.15	2.58	0.98	1.07	0.94
(Becomes *R&D intensity* in Model 4-6)	*(1.02)*	*(1.10)*	*(1.05)*	*(10.13)*	*(10.76)*	*(10.54)*	*(1.28)*	*(1.36)*	*(1.30)*
Industry asset cospecialization$_k$	−0.17	−0.36	−0.24	−0.25	0.11	−0.74	1.00	1.30	0.38
	(3.96)	*(3.87)*	*(3.88)*	*(3.09)*	*(3.06)*	*(3.09)*	*(5.54)*	*(5.61)*	*(5.48)*
Patents$_{ikt}$	0.23	0.23	0.23	0.23	0.25	0.22	0.15	0.15	0.13
	(0.20)	*(0.20)*	*(0.20)*	*(0.20)*	*(0.20)*	*(0.20)*	*(0.23)*	*(0.23)*	*(0.23)*
References to science$_{ikt}$	−0.84*	−0.79*	−0.79*	−0.93*	−0.99**	−0.88*	−1.04*	−0.96*	−0.95*
	(0.53)	*(0.54)*	*(0.54)*	*(0.56)*	*(0.57)*	*(0.57)*	*(0.68)*	*(0.68)*	*(0.68)*
Trademarks$_{ikt}$	−0.65**	−0.67**	−0.67**	−0.59*	−0.55*	−0.60*	−0.82**	−0.84**	−0.84**
	(0.37)	*(0.38)*	*(0.38)*	*(0.37)*	*(0.38)*	*(0.37)*	*(0.39)*	*(0.39)*	*(0.39)*
Public$_{it}$	0.69*	0.68*	0.67*	0.53*	0.34	0.49	0.48	0.45	0.43
	(0.42)	*(0.43)*	*(0.43)*	*(0.40)*	*(0.44)*	*(0.40)*	*(0.48)*	*(0.48)*	*(0.48)*
Firm age$_{it}$	1.90***	1.87***	1.86***	1.93***	1.85**	1.88***	2.45***	2.42***	2.44***
	(0.78)	*(0.78)*	*(0.79)*	*(0.78)*	*(0.80)*	*(0.79)*	*(0.88)*	*(0.88)*	*(0.88)*
Exit$_{it}$	−0.83*	−0.82*	−0.81*	−0.85*	−0.89*	−0.85*	−0.95	−0.96*	−0.95*
	(0.60)	*(0.60)*	*(0.60)*	*(0.60)*	*(0.59)*	*(0.60)*	*(0.74)*	*(0.74)*	*(0.74)*
Industry sales$_{kt}$	0.74	0.82	0.85				1.15	1.31*	1.36*
	(0.74)	*(0.76)*	*(0.76)*				*(0.96)*	*(0.99)*	*(1.03)*
Industry capital intensity$_{kt}$	−0.31	−0.41	−0.45	−1.68*	−1.96**	−1.89**	−0.42	−0.51	−0.47
	(0.99)	*(0.99)*	*(0.99)*	*(1.09)*	*(1.18)*	*(1.14)*	*(1.25)*	*(1.25)*	*(1.26)*
Constant	−11.82***	−11.97***	−11.85***	−4.36**	−4.41**	−4.15**	−12.30**	−12.86**	−13.04**
	(4.73)	*(4.70)*	*(4.60)*	*(2.09)*	*(2.08)*	*(2.02)*	*(7.25)*	*(7.12)*	*(7.10)*
Codevelopment experience$_{ikt}$ X industry absorptive capacity$_k$		−9.03*						−14.85***	
		(5.55)						*(5.07)*	
Codevelopment experience$_{ikt}$ X *R&D intensity*$_{kt}$					−12.89*				
					(9.77)				
Codevelopment experience$_{ikt}$ X industry asset cospecialization$_k$			33.68*			40.21***			44.79***
			(20.49)			*(16.38)*			*(18.60)*
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Number of obs.	12,845	12,845	12,845	12,845	12,845	12,845	5,523	5,523	5,523
Log likelihood	−461.65	−460.85	−460.84	−460.20	−459.07	−459.03	−349.60	−348.11	−348.41

Robust standard errors clustered at the firm-application industry level in parentheses. *** significant at 0.01; ** significant at 0.05; * significant at 0.1.
We dropped 'industry sales' from model 4-6 because it is highly collinear with 'industry absorptive capacity,' which in these models is measured as industry R&D over industry sales.
Number of firms in models 7-9 is 506. Thirteen firms were dropped from this sample estimation because we do not have data for their primary application industries (USPTO sequence = 56).
†: Controlled for by including the time averages of the time varying explanatory variables.

Table A3. Robustness analyses with split samples (pooled Poisson estimation)

Dependent variable: Number of out-licensing deals	Model 1 (Low industry absorptive capacity)	Model 2 (High industry absorptive capacity)	Difference (Testing H2)	Model 3 (Low industry asset cospecialization)	Model 4 (High industry asset cospecialization)	Difference (Testing H3)
Codevelopment experience$_{ikt}$	6.35***	0.78**	−5.57***	0.75**	5.68***	4.93***
	(1.80)	*(0.37)*	*chi2=9.26*	*(0.38)*	*(1.55)*	*chi2=9.56*
			p <0.01			*p <0.01*
Industry absorptive capacity$_k$	.	.		15.42***	−0.72	
				(1.67)	*(0.78)*	
Industry asset cospecialization$_k$	25.20***	−0.57		.	.	
	(2.68)	*(0.65)*				
Patents$_{ikt}$	0.31	0.28		0.34*	0.15	
	(0.42)	*(0.22)*		*(0.23)*	*(0.35)*	
References to science$_{ikt}$	−1.56***	−1.19**		−0.80	−1.98**	
	(0.55)	*(0.64)*		*(0.63)*	*(0.98)*	
Trademarks$_{ikt}$	−1.64***	−0.16		−0.22	−1.42**	
	(0.64)	*(0.38)*		*(0.38)*	*(0.63)*	
Public$_{it}$	0.98**	0.51		0.69*	0.56	
	(0.44)	*(0.43)*		*(0.44)*	*(1.35)*	
Firm age$_{it}$	−1.14*	2.38***		2.23***	1.10	
	(0.71)	*(0.85)*		*(0.93)*	*(1.14)*	
Exit$_{it}$	0.57	−1.21**		−1.21*	0.41	
	(0.55)	*(0.74)*		*(0.75)*	*(0.69)*	
Industry sales$_{kt}$	−7.21***	−0.12		−0.06	1.05	
	(2.05)	*(1.08)*		*(1.27)*	*(1.92)*	
Industry capital intensity$_{kt}$	−4.57*	−1.15		−0.87	−3.87**	
	(2.94)	*(1.45)*		*(1.78)*	*(2.31)*	
Constant	−49.87***	−10.13***		−25.46***	−7.34*	
	(7.94)	*(4.24)*		*(4.71)*	*(4.49)*	
Year dummies (1997-2007)	(Yes)	(Yes)		(Yes)	(Yes)	
Firm-application industry fixed effects†	(Yes)	(Yes)		(Yes)	(Yes)	
Number of obs.	6,413	6,432		5,823	7,022	
Log likelihood	−65.01	−374.83		−329.84	−112.09	

Robust standard errors clustered at the firm-application industry level in parentheses
*** significant at 0.01; ** significant at 0.05; * significant at 0.1
†: Controlled for by including the time averages of the time varying explanatory variables.
"." means the corresponding variable was dropped from estimation because of colinearity. The colinearity occurred because in the estimation we used the dummy form of the corresponding variables (1 if the corresponding variable is above the sample medium, and 0 if otherwise). When we use the continuous form of the corresponding variables, the results remain qualitatively unchanged.