KNOWLEDGE TRANSFER, LEARNING, AND COSPECIALIZED COMPLEMENTARY ASSETS: THE ROLE OF FIRM CAPABILITIES IN THE MARKETS FOR TECHNOLOGY

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ABSTRACT

We examine the classic decision faced by technology suppliers and buyers in the markets for technology: whether to compete in the product markets or cooperate through technology licensing. Prior research has indicated various factors that affect this choice, including the transaction costs of licensing, the strength of intellectual property protection rights, and the costs of acquiring complementary assets necessary to commercialize new technologies. We advance this literature by integrating into the analysis the effect of firm capabilities in transferring and absorbing knowledge and the conditioning role of cospecialized complementary assets. In particular, using a stylized bargaining model we hypothesize that the supplier's knowledge transfer capability stimulates licensing. However, the importance of this capability decreases when licensing to industries where the typical buyer has strong absorptive capacity. Knowledge transfer capabilities are instead critical when licensing to industries where R&D and downstream activities are cospecialized. We find empirical supports for these predictions using an unbalanced panel data set with information on the licensing strategies of the population of U.S. "serial innovators," e.g. firms with less than 500 employees and a sustained innovative activity, as evidenced by their patent holdings.

Key Words: technology licensing, markets for technology, cospecialized complementary assets, absorptive capacity, knowledge transfer capabilities.

INTRODUCTION

In recent decades, the grounding of technologies in science, a strengthening of

appropriability, and advances in computer software have together facilitated the expansion of

markets for technology and, in particular, contract-based technology licensing exchanges (Arora,

Fosfuri, and Gambardella, 2001; Arora and Gambardella, 2010; Oxley, 1999). The result is an

improved division of labor between the production and use of technology across firms, as well as

the substantial growth of markets in which firms trade technology through licensing and other

forms of cooperative alliances. In fact, between 1996 and 2006 the value of technology

exchanges within OECD nations as a percentage of GDP has increased by 63% (OECD, 2009).

Despite its importance for technology development and commercialization, technology

licensing is still not a central activity in corporate strategy and is limited to certain industries

such as biopharmaceuticals and electronics. Understanding what facilitates and limits the

markets for technology has therefore been an important objective of recent strategy research. For

instance, recent research has suggested that the costs of acquiring complementary assets

necessary to commercialize new technologies, the strength of intellectual property rights (IPR)

protection, and the interaction between IPR and ownership of specialized complementary assets

are critical determinants of the suppliers' incentive to license out their innovations (Arora and

Ceccagnoli, 2006; Gans and Stern, 2003). Additionally, different kinds of transaction costs limit

licensing (Ceccagnoli *et al.*, 2010; Fosfuri, 2006; Gambardella, Giuri, and Luzzi, 2007) and

increases the likelihood of vertical integration (Williamson, 1979).

One of the main limitations of the current literature is that it primarily focuses on the

supply-side of the markets, while the demand-side of licensing is inadequately taken into account

(Arora and Gambardella, 2010). Except for transaction costs incurred by both suppliers and

buyers, the major factors driving licensing such as the costs of acquiring complementary assets and the strength of intellectual property rights are primarily concerns for technology suppliers. A deeper understanding of licensing, however, requires a more explicit analysis of the concerns of the potential buyers (Arora and Gambardella, 2010). We thus adopt a holistic view of licensing, by developing and estimating a stylized theoretical model that incorporates incentives to commercialize technology from both the demand and supply side, in the spirit of Gans et al. (2002). One of the main advantages of our modeling approach is it provides the opportunity to integrate the role of firm capabilities in technology commercialization, along the lines of earlier literature on technology transfer and international business (Contractor, 1981; Teece, 1977).

The cornerstone of our study is based on the idea that a key concern of technology buyers is the cost of integrating an external technology into their products and value chains. We argue that such integration costs are critically conditioned by firm capabilities. First, the suppliers' capability of transferring knowledge is important in lowering the buyers' integration costs (Contractor, 1981; Teece, 1977) and is thus a key driver in technology licensing. Second, integration costs can alternatively be lowered by the buyers' absorptive capacity – i.e., the ability to understand, integrate and exploit external knowledge (Cohen and Levinthal, 1989). As such, we argue that the suppliers' knowledge transfer capabilities are less critical when licensing to an industry where the typical potential buyer has strong absorptive capacity. This idea parallels the earlier finding from the markets for technology literature that international technology transfer benefits from bundling patent licensing with the transfer of know-how, especially when the buyer is located in less developed countries (Arora, 1996).

Our emphasis on buyers' integration costs also allows us to revisit the role of the nature of complementary assets required to commercialize innovations in affecting firm boundaries.

Drawing on both the economic and management literature (Milgrom and Roberts, 1990; Teece, 1986), we argue that in industries where complementary activities such as manufacturing/marketing are cospecialized with R&D, it is more costly for a firm to integrate an external technology than using an internally generated technology. Essentially, the use of an external technology acquired through an arm's length transaction breaks up the mutually dependent R&D and supporting activities and tends to create inefficiencies in technology transfer. This idea indicates that cospecialization between R&D and downstream activities reduces efficiency in commercializing a technology across boundaries of firms. More interestingly, we find that this inefficiency can be overcome by the technology supplier's strong knowledge transfer capabilities. This suggests a positive interaction effect between cospecialized assets and suppliers' knowledge transfer capabilities on licensing.

We find empirical support for our theoretical model using a representative sample of U.S. technology-based firms with fewer than 500 employees. This sample is derived from the Chi Research/Small Business Administration (SBA) database containing 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 *et al.*, 2003; Hicks and Hegde, 2005). We integrated this data set with information gathered from multiple additional sources including the SDC Platinum alliances database available from Thomson Reuters, USPTO trademarks and patents data, Compustat, and the Carnegie Mellon Survey on industrial R&D. The result is a dataset that includes information on the licensing strategies of a set of 519 small, but patent intensive, public and private U.S. companies with patents applicable in a broad range of industries (38 "application industries") over a time period between 1996 and 2007.

The key feature of our empirical strategy relies on the use of panel data fixed effects models. We observe the number of licensing deals made by the focal technology supplier i in the potential application industry k observed at time t. We identify the potential application industries from the focal firm's patents by exploiting the concordance between the technology classes assigned to the firm's patent and the SIC product classification maintained by the U.S. Patent Office. This concordance allows us to exploit a substantial cross-industry variation in our measures of cospecialization and absorptive capacity, which are measured at the level of the application industry. These, along with a measure for the supplier knowledge transfer capability that varies across firms, application industries, and time, provide a key source of identification to test our propositions.

The paper is organized as follows. In the next section, we present our stylized model and a set of testable propositions. We then specify our empirical model and test our theoretical predictions using panel data methods. The last section contains the discussion of the results and conclusions.

THEORY AND PROPOSITIONS

Licensing is an important strategy for innovators in exploiting their technologies. The literature of markets for technology has focused on the role of IPR and the nature of complementary assets in affecting the supply-side of these markets. In order to integrate the role of firm capabilities into this framework, we use 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, i.e., selling the inventions to incumbent firms of this industry ("buyers", "incumbents", or "licensees"). The incumbents can then incorporate the inventions

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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 in-house. The latter entails the investment of forward integration. The decision tree below characterizes the expected payoffs from this decision with reference to both the supplier and a typical potential buyer.

$$\text{Supplier}$$

License   Forward integrate

$$\tau - c$$
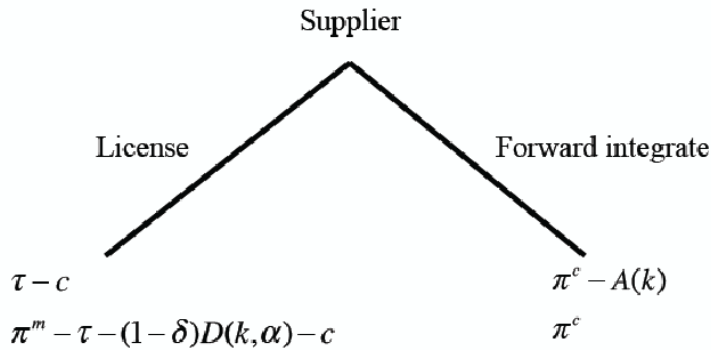$$\pi^m - \tau - (1-\delta)D(k,\alpha) - c$$

$$\pi^c - A(k)$$
$$\pi^c$$

Figure 1: Decision tree

In this decision tree, we incorporate some of the key drivers in the licensing/forward integration decision highlighted by prior research.[1] The first is the cost (A) for the technology supplier to acquire complementary assets (manufacturing, sale, and service) if it chooses forward integration. It's well known that in sectors where complementary assets are costly to acquire, entrepreneurial firms are more likely to avoid duplicating these assets and ally with incumbents that already possess them (Gans *et al.*, 2002; Teece, 1986). A classic example is the sustained licensing activity in the biopharmaceutical industry between biotech start-ups (which lack complementary assets) and large pharmaceutical companies (Gans and Stern, 2003). Furthermore, the costs A are a function of asset cospecialization (k), e.g., the extent to which forward integration in the product market requires specialized/cospecialized (or sunk) production

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[1] Some important features such as the possibility that the incumbent can choose whether to imitate the entrepreneurial firm's invention, as in the model of Gans et al (2002), are made in a more general model that is available from the authors upon request. Since our main results are unchanged, we choose the simplified model structure to better understand the underlying intuitions.

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facilities or marketing channels. These assets are hard to acquire for a small firm and are typically developed over time, thus increasing the costs for small firms to compete with incumbents (Teece 1986; Gans and Stern 2003).

Other parameters that enter the licensing decision include the profits from commercializing the technology, licensing fees and transaction costs (e.g., Gans *et al.*, 2002). The transaction costs, *c,* include the costs of negotiating and enforcing the license.[2] If the negotiation succeeds, the seller earns a licensing revenue τ paid by the incumbent. The incumbent commercializes the technology in the market place and earns monopoly profits π^m. If the seller decides to vertically integrate into the application industry instead of licensing, the seller will face competition from the incumbent in the product markets and earns a profit of π^c. For simplicity, one can assume the incumbent also earns a profit of π^c from competing downstream.

Thus in this simplified framework, licensing will take place if the gains from the trade outweigh the costs. As in Gans et al.'s (2002) model, the gains from trade are due to the avoidance of product market competition and the avoidance of duplicative costs of acquiring downstream assets. However, a distinguishing feature of our model is that the gains from trade can 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 with the Gans et al.'s (2002) model is that we introduce the integration costs for licensing, *D*, and a capability parameter of the seller, i.e., δ, the seller's knowledge transfer capability.

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[2] We suppose 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 holdup that may reduce the incentives for licensing. However, since this is not the key mechanism driving our results, we keep the model as simple as possible and note that relaxing this assumption does not affect our main predictions.

Integration costs are defined as the expected costs for incumbents in an application industry to integrate the supplier's technology. Certainly, technology-specific factors can contribute to these costs, such as the maturity of the technology or the requirement of expensive equipment. What is less obvious, but critical to the integration costs, is the nature of the application industry. Indeed, two important characteristics of the application industry will affect the integration costs. The first is α, i.e., the absorptive capacity of the typical buyer. Absorptive capacity is the ability to acquire, assimilate, and exploit knowledge created outside an organization (Cohen and Levinthal, 1989, 1990). It is often a result of continuous research and development targeted towards monitoring and learning new developments by other organizations. Organizational routines may also be developed to productively assess and exploit external technologies (Lane, Koka, and Pathak, 2006). Thus the buyers' absorptive capacity is a function of their R&D investments, organizational routines, and exogenous characteristics that Cohen and Levinthal (1989) define as "the ease of leaning" from the external environment. The latter can be determined by the complexity of outside knowledge to be assimilated and the degree to which the knowledge is targeted to the needs and concerns of potential buyers. If a typical potential buyer has weak absorptive capacity, as a result of the above environmental conditions, internal R&D decisions, and routines, we can expect that the buyer's cost of integrating external technologies will be high.

The second source of integration costs is k, the degree of cospecialization between R&D and downstream activities in the application industry. As an example of such cospecialization, a new product design may require the use of specialized manufacturing assets and thus a close coordination with manufacturing personnel; on the other hand, when changing their manufacturing process, firms may need to ensure it is compatible with their special R&D outputs

(Teece, 1986). For industries that feature such cospecialization, successful commercialization may require proximate, tight, and frequent communication links between personnel from R&D and manufacturing and/or marketing. Such interdependencies, highlighted by a number of scholars, including Rosenberg and Kline (1986), give rise to complementarity across activities in the value chain (Milgrom and Roberts, 1990). When these complementary activities are performed in two separate firms, coordination costs will arise, thus increasing the cost of integrating the focal technology into the buyer's value chain. These inefficiencies go beyond the potential for hold up that arises 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 effectively transfer it to buyers (Shane, 2004). We define a supplier's knowledge transfer capability as the ability to identify and communicate the value of its technology and 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 experiences, that effectively facilitate the identification of buyers' special needs and communication of know-how to buyers (Kogut and Zander, 1993). The ability to transfer knowledge to buyers has been somewhat neglected by the recent markets for technology literature, but has been found to be highly important in several settings, and in particular for the successful international expansion of multinational firms (Martin and Salomon, 2003).

We argue that suppliers' knowledge transfer capabilities are highly important for their technology licensing 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.

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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). Incumbents are also found to create information filters that absorb only the information that appears valuable to existing operations (Henderson and Clark, 1990). Thus, to help these incumbents understand the value of a novel invention, the seller needs to penetrate such information filters and be able to communicate how the invention may add value to their products or markets.

Second, sellers' knowledge transfer capabilities will assist buyers in lowering their integration costs. Even if a buyer understands the value of the new technology, integrating a novel and external 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 effectively combine the new technology with existing operations and to use it in their specialized manufacturing contexts. That is when the supplier's knowledge transfer capability is critical. Inventors' knowledge of how to reproduce and adapt the inventions in different contexts can greatly facilitate integration (Arora, 1995). Inventors' experiences with failed experiments or knowledge about under what environments the technology works best, if effectively codified or communicated to buyers will eliminate many uncertainties and unnecessary trial-and-errors 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

Our model suggests that licensing takes place if it generates a higher payoff relative to the forward integration option. Figure 1 shows the payoff functions of the technology supplier and a typical potential buyer or an incumbent. If the technology supplier chooses forward integration in

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the product market, the payoff will be $\pi^c - A(k)$. Meanwhile, the incumbent will earn π^c. On the other hand, if the technology supplier chooses licensing, it will negotiate with the incumbent for a licensing price τ. If the negotiation succeeds, the supplier will earn τ - c, and the buyer will earn $\pi^m - \tau - D(k,\alpha)(1-\delta) - c$.

The price τ that the buyer pays for the technology is determined by the Nash bargaining solution (Nash 1950). Under this solution, the price maximizes the parties' joint net gains from the negotiation, i.e., the two parties both earn more from cooperating than from competing. In equilibrium, the price is:

$$\tau^* = \max_{\tau} \left\{ \underbrace{[\tau - c - \pi^c + A(k)]^b}_{\text{supplier's net gains from licensing}} \times \underbrace{[\pi^m - \tau - (1-\delta)D(k,\alpha) - c - \pi^c]^{1-b}}_{\text{buyer's net gains from licensing}} \right\}$$

where b represents the bargaining power of the supplier.

Solving for the value of τ that maximizes the joint returns to licensing we obtain

$\tau^* = b\left[\pi^m - \frac{1-b}{b}A(k) - (1-\delta)D(k,\alpha) - \frac{1-2b}{b}(c + \pi^c)\right]$. Note that a stronger bargaining power of the technology supplier increases the equilibrium licensing price and thus the supplier incentive to out-license. However, the higher price will reduce the buyer's incentive to in-license. In fact, in equilibrium the bargaining power of the parties do not affect their likelihood of reaching an agreement. Thus for simplicity, we assume the two parties have an equal bargaining power (b=0.5), so that above simplifies to $\tau^* = 0.5[\pi^m - A(k) - (1-\delta)D(k,\alpha)]$. The supplier's licensing revenue thus increases with the buyer's monopoly profit from technology commercialization and decreases with the buyer's integration costs and the supplier's costs of forward integration. Therefore, we can compute the technology supplier's net gain from licensing relative to vertical integration:

$$\Delta = \pi^L - \pi^{NL} = \frac{\pi^m - 2\,\pi^c}{2} - c + \frac{A(k)}{2} - \frac{(1-\delta)D(k,\alpha)}{2}.$$

A licensing agreement will take place as long as $\Delta \geq 0$. It is easy to verify that this

condition is equivalent to

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

The supplier's likelihood of licensing increases with the net gain from licensing relative to

vertical integration. The latter is in turn a function of several parameters. Our particular interest

is the marginal effect of an increase in the supplier's knowledge transfer capability on the

decision to license. We can therefore formulate the following proposition.

Proposition 1*: A technology supplier's knowledge transfer capability increases the supplier's returns*

from licensing relative to forward integration, and therefore increases the likelihood of licensing.

Proposition 1 can be easily proved by noting that $\frac{\partial \Delta}{\partial \delta} = \frac{D(k,\alpha)}{2} > 0$. The primary intuition

for this positive effect is that the seller's knowledge transfer capability facilitates the buyer's

integration of the licensed technology, therefore increasing the payoffs from licensing for both

parties.

Our simplified model also suggests that the effect of the supplier's knowledge transfer

capability is conditioned by two characteristics of the application industry for the technology: α

and k. In particular, we formulate the following propositions.

Proposition 2*: The importance of a technology supplier's knowledge transfer capability for licensing*

decreases with the absorptive capacity of buyers in the application industry.

Proposition 3*: The importance of a technology supplier's knowledge transfer capability for licensing*

increases when the downstream activities required for technology commercialization in the application

industry are cospecialized with R&D.

Formally, Proposition 2 is based on negativity of the cross partial derivative $\frac{\partial^2 \Delta}{\partial \delta \partial \alpha} = \frac{1}{2}\frac{\partial D(k,\alpha)}{\partial \alpha} < 0$, whereas Proposition 3 is based on the positivity of $\frac{\partial^2 \Delta}{\partial \delta \partial k} = \frac{1}{2}\frac{\partial D(k,\alpha)}{\partial k} > 0$. Intuitively, for an application industry where the typical buyer has strong absorptive capacity, integration costs are expected to be low. As a result, the seller's knowledge transfer capability is relatively less important for establishing a licensing agreement. In contrast, for an application industry requiring cospecialization between R&D and downstream activities, the costs of adapting and integrating the supplier's technology would be relatively high. The supplier's knowledge transfer capability would then be especially helpful to lower the integration costs for buyers.

EMPIRICAL MODEL

Model Specification and Estimation Methods

Our empirical model can be derived by noting that the probability that a technology supplier i licenses a technology j, at time t, in application industry k, is a function of the payoff from licensing. The payoff is partly observed by the econometrician at the firm and application industry level in any given year, but is *unobserved at the level of the focal technology*, e.g. the technology held by the supplier underlying the potential transaction. In light of our theoretical predictions and available data, we specify the net benefit from licensing as follows:

$$\Delta_{jikt} = \boldsymbol{x}'_{ikt}\beta + \boldsymbol{z}'_{k}\gamma + \boldsymbol{w}'_{1kt}\rho_1 + \boldsymbol{w}'_{2it}\rho_2 + \eta_t + \varepsilon_{jikt}. \ (1)$$

The net payoffs from licensing (Equation 1) are a function of a set of parameters to be estimated $(\beta, \gamma, \rho_1, \rho_2)$, and a list of variables below. Note that k corresponds to an application industry in a subset of K total application industries of the population, with each subset most likely to differ across supplier i because each supplier has different technologies.

1) x_{ikt} includes the observed firm characteristics that vary both over time and across

   application industries. An example is one of our main variables of interest: the knowledge

   transfer capability that the technology supplier develops over time and towards a specific

   application industry.

2) Observed characteristics that are specific to a supplier's application industry (z_k). This

   set includes two variables used to test propositions 2 and 3: the expected absorptive

   capacity of a typical incumbent in industry k, and the cospecialization between R&D and

   downstream activities in this industry.

3) Other firm and application industry controls, some of which vary across k and t (w_{1kt}),

   such as the size of the market); others vary across i and t (w_{2it}), such as firm age

4) Unobserved effects that only vary over time η_t.

5) An unobserved technology specific effect, ε_{jikt}, which represent zero-mean random

   shocks that drive the gains from licensing and that are specific to the focal technology.

   Thus this effect varies across all dimensions.

The expected probability of licensing for technology supplier i, at time t, in application

industry k, can then be specified as follows:

$$\Pr_{ikt}(\text{Licensing}) = Pr(\Delta_{jikt} > 0) = F(x'_{ikt}\beta + z'_k\gamma + w'_{1kt}\rho_1 + w'_{2it}\rho_2 + \eta_t), (2)$$

with F being a symmetric cumulative distribution function for ε_{jikt}. In other words, the

unobserved components of the gains from trade and transaction costs at the technology level are

conditioned out. As such, licensing for firm i in application industry k and year t will be expected

to occur with the probability specified in equation (2).

We can then derive the expected number of licensing agreements of firm i in the potential

application industry k and time t, LIC_{ikt}, as a function of the probability of licensing times the number of technologies that could potentially be licensed, T_{ikt}, e.g.:

$$LIC_{ikt} = F(\boldsymbol{x}'_{ikt}\beta + \boldsymbol{z}'_k\gamma + \boldsymbol{w}'_{1kt}\rho_1 + \boldsymbol{w}'_{2it}\rho_2 + \eta_t) * T_{ikt}. \quad (3)$$

Note that T_{ikt} is unobserved. However, we do observe the number of granted patents held by the technology supplier i in the application industry k and year t, P_{ikt}. A granted patent indeed represents, in most cases, a necessary condition for technology licensing, especially in the manufacturing sector (Arora and Ceccagnoli, 2006). As we will discuss later, it is also possible to identify the potential set of application industries of each firm's technology by analyzing the technological classes of a patent, as determined by the USPTO. Moreover, since our dependent variable LIC_{ikt}, the number of licenses, is discrete and non-negative, we use a Poisson model. The model also takes into account equation (3)'s non-linear nature and the unobserved heterogeneity on the right-hand-side of the equation. As such, the expected value of our dependent variable is specified as an exponential function of the number of patents P_{ikt} and the variables driving the probability of licensing in equation (2):

$$E(LIC_{ikt}|\boldsymbol{x}_{ikt}, \boldsymbol{z}_k, \boldsymbol{w}, \eta_t, P_{ikt}) = \exp(\boldsymbol{x}'_{ikt}\beta + \boldsymbol{z}'_k\gamma + \boldsymbol{w}'_{1kt}\rho_1 + \boldsymbol{w}'_{2it}\rho_2 + \tau P_{ikt} + \eta_t), \quad (4)$$

where $\beta, \gamma, \rho_1, \rho_2$ represent vectors of parameters to be estimated. To test propositions 2 and 3, we interacted the knowledge transfer capability variable which is included in $\boldsymbol{x}_{ikt}$ with the measures of absorptive capacity and asset cospecialization included in $\boldsymbol{z}_k$.

We use standard errors that are robust to overdispersion and clustered by firms and their respective application industries, e.g. the panel level for which we have repeated measures over time because our dependent variable has a higher variance than its mean, as shown in Table 1. We also experimented with a higher level of clustering, e.g. the firm-level, and obtained very

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similar results.

Note that potentially unobserved firm-fixed effects in application industry k may be correlated with some of the right-hand-side variables of equation (4), leading to estimation biases. To address this issue, we estimate equation (4) using a pooled Poisson quasi-maximum likelihood model (QMLE) with a Chamberlain-Mundlak correlated random effect device (Wooldridge, 2010). This method controls for panel-specific unobserved effects using the averages of all explanatory variables across years within each panel (defined by firm i in industry k). Formally, we assume the existence of an unobserved effect, c_{ik}, equal to:

$$c_{ik} = exp\big(\psi + \overline{\boldsymbol{x}}'_{ik}\tilde{\beta} + \overline{\boldsymbol{w}}'_{1k}\tilde{\rho}_1 + \overline{\boldsymbol{w}}'_{2i}\tilde{\rho}_2 + \tilde{\tau}\overline{P}_{ik}\big)a_i, \qquad (5)$$

where ψ is a constant and a_i is uncorrelated with the covariates in (4) and has unit mean. This amounts to adding the time averages of the time-varying explanatory variables as a set of covariates in (4). As a robustness check, we used the same method for population average and random effects Poisson models; we also estimated the conventional fixed effects Poisson model, which conditions c_{ik} out prior to estimation.

Finally, a Poisson model implies that the estimated coefficients have a semi-elasticity interpretation. That is, the estimated coefficient of an independent variable represents the percentage change in the expected count of the dependent variable for a unit change in the independent variable. Since we use the natural log of our main independent variables of interest, the estimated coefficients of these variables can be interpreted as standard elasticities, thus also providing information about the magnitude of the effects of interest. We provide additional quantitative information on the effect of the interacted variables for the benchmark specification in Table 3.

Data and Sample

To test our propositions, we construct 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. Sample firms' patented inventions are taken from the small firm patent database constructed by Diana Hicks and Chi Research Inc. and sponsored by the Office of Advocacy of the Small Business Administration (SBA). We also supplement this data with the NBER patent database and Thompson Delphion patent database. Additionally, we collect sample firms' trademark data from the USPTO trademarks database. Sample firms' potential application industries are based on the patent data mentioned above as well as the USPTO patent-industry concordance file generated in 2005. Measures of absorptive capacity and asset cospecialization in the potential application industries are obtained using the 1994 Carnegie Mellon Survey on industrial R&D, summarized in Cohen et al. (2000). We also used Compustat to identify potential market size and average R&D intensity in the potential application industry.

The Chi Research-SBA patent database, in particular, defines our sample. This data set contains detailed patent information on the population of more than 1,200 private and public U.S. companies that generated at least 15 patents between 1998 and 2002. The strength of this database is that in identifying these companies, all establishments and subsidiaries were unified with the ultimate parent company and their patents counted towards the parent patent count.[3] These firms have been defined as the population of U.S. "serial innovators," e.g., technology-

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[3] Obtaining 15 patents in a 5-year window for a small firm reflects a strong innovative performance. The threshold was necessary to ensure accurate firm identification for, essentially, the entire population of inventive firms in the U.S. (Hicks 2002). This is due to both the challenges of name-matching patentees to the ultimate parent and the high volatility among small firms, which are acquired or disappear regularly. In other words, substantial work must be done to ensure that the patentees were in business and independent, etc. Ignoring this point will compromise the integrity of the results (Tether, Smith and Thwaites 1997).

based firms that were able to sustain innovation beyond the first great idea upon which the firm was founded (CHI-Research, 2003; Hicks *et al.*, 2003; Hicks and Hegde, 2005). From this database we selected only the small firms (e.g., those with fewer than 500 employees). Our final sample is based on an unbalanced panel of 519 technology-based small firms with non-missing values for the measures used in the empirical analysis. Among the top innovators in our database, are several pharmaceutical and information technology firms that vary in their emphasis on licensing.[4]

We identified the application industries in which the patents of the small serial innovators could be potentially used by exploiting the concordance developed and maintained by the U.S. Patent and Trademarks Office's (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 use the new patented processes in the manufacture of their products (the list of these sequence codes and corresponding SIC codes is contained in the Appendix).[5] Thus, for each firm in our sample, we collected a list of sequence codes corresponding to the primary technology class of its patents as potential application industries

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[4] Among the top innovating firms in our database we find pharmaceutical firms such as Isis, Alliance, Neurogen and NPS. These are small (less than 500 employees) public companies with a sustained record of innovation. Each has a core technology around which their R&D is focused. Alliance has perfluorochemical technology; Isis has antisense RNA-based technology; NPS has calcium receptor technology, and Neurogen has a technology it calls the Accelerated Intelligent Drug Discovery platform. There are also small information technology companies that figure among the top patentees in our data set. Candescent and Tessera are examples. Candescent owns patents on thin cathode-ray tube technology and focuses on a licensing business model. Tessera has semiconductor chip-scale packaging technology for demanding applications that finds its way into advanced consumer electronics devices. It earns money licensing its technology and has successfully litigated its patents against big firms (Chi Research Inc. 2003).

[5] Each of these sequence codes corresponds to one or more two- to four-digit Standard Industry Classification codes. An excerpt of the concordance is available at http://www.uspto.gov/go/taf/brochure.htm. 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 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."

and built a panel dataset with repeated observations over time of each sample firm in each of its potential application industries. As explained below, key firm-level variables such as the number of licensing deals, patents granted, trademarks registered, and codevelopment alliances will vary by firm, sequence codes, and years, with the firm-sequence code representing the main panel variable.

Main Variables

Out-licensing$_{ikt}$. Our dependent variable, *Out-licensing$_{ikt}$*, 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 was not clear on which firm was the supplier, we complemented our search through online archival news. In a second step, we used the above information to determine the application industry involved in the licensing using both the SIC industry code of the alliance assigned by SDC and the analysis of the synopsis.

Each sample firm made from zero to eight outlicensing deals each year to each of its application industries. A summary of statistics and correlations for this variable (as well as the remaining variables detailed below) are presented in Table 1.

****
Insert Table 1 Here
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Codevelopment Experience$_{ikt}$. We measure a firm's knowledge transfer capability with its *Codevelopment Experience$_{ikt}$*, i.e., the cumulated number of times a sample firm *i* participated in joint R&D alliances by year *t*, in which the focal firm's technologies were used to develop

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applications for industry *k*. The logic underlying this measure is that firms gain efficiency and capability in an action by repeating it over time, similar to many other types of alliances and activities (Teece, Pisano, and Shuen, 1997; Zott, 2003). Codevelopment activities relate to basic information sharing, technical assistance, and trust/reputation building. Repeated experiences in such activities are likely to be associate with a stronger ability to coordinate and communicate with partners and to develop trust for knowledge sharing (Schreiner, Kale, and Corsten, 2009). Thus, firms with more codevelopment experience are likely to be better at technical assistance and knowledge transfer across firm boundaries. We compute the stock of codevelopment activities using a 15% discount rate. We also use the simple cumulated count as a robustness check. The data of codevelopment activities again come from the SDC database which provides an indicator for deals with joint R&D agreements. We read through the deal synopsis to select only transactions that involved the focal firm's technology in order to ensure that the focal firm was active in knowledge transfer in the transactions.

(Codevelopment experience X Industry Absorptive Capacity)$_{ikt}$. To test Proposition 2, we interact a firm's knowledge transfer capability with the absorptive capacity of the typical buyer in the application industry (*Industry Absorptive Capacity$_k$*). We measure the latter from the Carnegie Mellon survey on industrial R&D (CMS), which contains a measure of the percentage of R&D effort devoted to learning novel external knowledge from a sample of 1,477 business units operating in a broad range of industries.[6] We matched the SIC codes of these business units to the USPTO sequence codes and computed the averages of the CMU absorptive capacity measure for each sequence code (i.e., application industry k). Note that this survey-based measure is time-invariant, thus its main effect will not be estimated in a fixed-effect model.

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[6] 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?"

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Nevertheless, we can still identify the coefficient of the interaction term *Codevelopment experience X Industry Absorptive Capacity* because the latter is time-variant, allowing us to test Proposition 2.

As a robustness check, we used an alternative measure for absorptive capacity that varies across both time and application industries. Cohen and Levinthal suggest that a firm's absorptive capacity is partly determined by its R&D investment, hence its dual role: the first serves to introduce new or improved products and processes; the second allows the firm to better exploit external knowledge flows (Cohen and Levinthal, 1989). Therefore, we calculated each application industry's yearly R&D intensity (weighted by sales) obtained from Compustat (*R&D intensity$_{kt}$*).[7]

(Codevelopment experience X Industry Asset Cospecialization)$_{ikt}$. To test Proposition 3 we interact a firm's knowledge transfer capability with the firm's application industry's asset cospecialization (*Industry Asset Cospecialization$_k$*). We measure asset cospecialization based on the frequency of face-to-face interaction between personnel from R&D and marketing or manufacturing units, as in Arora and Ceccagnoli (2006). This measure is based on the idea that when innovation and downstream assets are cospecialized, ongoing mutual adjustments between the two are necessary for commercialization (Kline and Rosenberg, 1986; Teece, 1992). Put differently, and drawing on the economic notion of complementarity, our measure reflects the degree of organizational complementarity between upstream and downstream activities in the value chain. This is consistent with Teece's (1986) notion of bilateral dependence between the technology to be commercialized and the complementary assets required for its

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[7] Note that a limitation of this measure is that it is only available for public firms. However, potential buyers in our theory are industry incumbents with downstream capabilities, which indeed are very likely to be both large and public.

commercialization.[8] The data come from the CMU survey data. We computed the share of respondents (among the 1477 business units) in which R&D and marketing/manufacturing personnel interacted daily for each application industry (the median frequency was weekly) and matched them to our panel based on the sequence code corresponding to each application industry k.[9] Although the survey was conducted in the pre-sample period (i.e., in 1994), the importance of complementary assets in profiting from innovation has been shown to change slowly over time (Ceccagnoli and Rothaermel, 2008; Cohen, Nelson, and Walsh, 2000).

Control Variables

Patents$_{ikt}$. We control for the stock of technologies available for commercialization, i.e., the P_{ikt} in equation (4). The measure is firm i's stock of U.S. patents as of year t potentially useful for industry k. We use the depreciated stock of patents with a discount rate of 15% (Hall, Jaffe, and Trajtenberg, 2005).

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; Arora and Gambardella, 1994; Teece, 1977; von Hippel, 1994). From this perspective, codifiability may facilitate licensing. On the other hand, a more codified technology may increase the risk of negotiating a license. Such a technology, once disclosed to potential buyers, is relatively easy for them to replicate and invent around. Tacit knowledge, in contrast, can better exclude others from misappropriating it (Teece, 1986). We control for these possible effects of technology codifiability using a common proxy based on patents' backward references to science publications (Narin, Hamilton, and Olivastro, 1997).

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[8] Teece's himself has recently emphasized the interconnections between the concept of cospecialization and complementarities across activities in explaining the boundaries of the innovating firm (Teece, 2010).
[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?" Responses were coded utilizing a 4-point Likert scale corresponding to daily, weekly, monthly, rarely, or never.

Specifically, the measure is computed as the percentage of science references among all references made by a firm i's patents that were granted in year t and useful for industry k.

Trademarks$_{ikt}$. We control for a sample firm i's downstream capabilities using the number of trademarks registered by year t and in application industry k. Trademarks can be thought of as an important measure of marketing capabilities (Ceccagnoli *et al.*, 2010; Fosfuri, Giarratana, and Luzzi, 2008; Gambardella and Giarratana, 2008; Huang *et al.*, 2009). According to the USPTO, a trademark "identifies and distinguishes the source of the goods or services of one party from those of others." It clearly indicates a firm's ability to market its products. Indeed, firms would not be able to sustain its trademarks without being able to build on the firm's distinctive identity in the product markets (Fosfuri and Giarratana, 2009; Fosfuri *et al.*, 2008; Mendonca, Pereira, and Godinho, 2004). We collect the trademark data for each sample firm from the USPTO CASSIS Trademarks BIB database. Since trademarks are classified by product classes, we then assign trademarks to each application industry k defined by the sequence codes, to obtain a measure that varies by i, k, and t.[10] We calculated the depreciated stock of trademarks with a discount rate of 15%, as we did for our patent stock measure. We expect *Trademarks$_{ikt}$* to have a negative effect on licensing because, according to our model, stronger marketing capabilities indicate a lower cost of acquiring complementary assets and forward integration for the technology supplier.[11]

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[10] Goods and services protected by trademarks are classified into 42 international classes, most of which can be easily linked to 2-digit SIC and industry sequence codes (http://www.uspto.gov/faq/trademarks.jsp#Application018). For the trademark classes that can be assigned to multiple sequence codes, we used a "fractional count" method analogous to the way the USPTO counts patents by SIC codes for their "Patenting Trends in the United States" reports (http://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_pat_tr.htm#PATR), when a patent class can be assigned to multiple SIC industries. For example, since class 11 of the trademark classification, 'Environmental control apparatus', can be assigned to two sequence codes, 38 and 55 ('Electrical lighting and wiring equipment" and professional and scientific instruments'), we assigned 50% of new trademarks registrations with a class code of 11 to each of the two sequence codes. The full concordance is available from the authors upon request.

[11] A more general model that allows for the threat of imitation by application industry incumbents suggests, however, that the technology supplier's downstream capabilities may reduce the threat of technology expropriation

Other firm characteristics. We control for whether a sample firm is publicly traded or privately owned (*public$_{it}$*) during our study period. One reason to include this control is that public firms are more likely to promptly announce their licensing deals. Consequently, we may be more likely to observe licensing deals by public rather than private firms. We also control for the age of a firm in year *t* (*firm age$_{it}$*); because as a firm gets older, it may build up more downstream resources and rely less on licensing as commercialization strategy. Finally, a dummy variable (*exit$_{it}$*) indicates whether a firm *i* went bankrupt, was acquired by, or merged with another firm 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 division or labor in markets for technology is conditioned by the number of potential buyers and their product market size. To control for these effects, we obtained from Compustat the total sales of public firms in application industry *k* in year *t* (*industry sales$_{kt}$*). We also control for the capital intensity of application industry *k* in year *t* (*industry capital intensity$_{kt}$*). The data were converted in 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 control for the unobserved heterogeneity that is time invariant and firm-application industry specific using the average of all explanatory variables across years. We also include a set of year dummies to control for time-varying unobserved effects on firms' licensing (η_t) during the 1996-2007 period.

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due to licensing and thus have a positive offsetting effect on the incentives to license. The model extension is available from the authors upon request.

RESULTS

Benchmark Results

Table 2 shows the results from estimating the pooled Poisson QMLE model with unobserved heterogeneity. In Model 1 we include our main independent variable of interest along with all the controls, to test Proposition 1. The effect of *codevelopment experience$_{ikt}$* on licensing is positive and significant at the 5% significance level. The magnitude of the coefficient represents a standard elasticity, indicating that a one percent increase in a firm's codevelopment experiences would yield a 0.8 percent increase in the firm's outlicensing, thus supporting Proposition 1.

To test Proposition 2 we introduce the interaction of *codevelopment experience$_{ikt}$* with *industry absorptive capacity$_{ik}$* in Model 2 of Table 2. The coefficient of this interaction term is negative and statistically significant, consistent with Proposition 2. To test Proposition 3 we introduce the interaction of *codevelopment experience$_{ikt}$* with *industry asset cospecialization$_{ik}$* in Model 3. The coefficient of this interaction term is positive and statistically significant, thus consistent with Proposition 3.

To examine the interaction effects in more detail, we computed and compare the marginal effects of *codevelopment experience* at different levels of *industry absorptive capacity* and *industry cospecialization* in Table 3. The second column of this table shows that 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 outlicensing activity, the elasticity drops to 1.4 percent (p<0.01) when *industry absorptive capacity$_k$* is one standard deviation above its mean. The change in the elasticities is significant at the 1% significance level, lending support for Proposition 2, since the

importance of a firm's knowledge transfer capability is reduced when the potential buyers' absorptive capacity is higher.

We also find support for Proposition 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 on average a one percent increase in a firm's codevelopment experience yields a 3.7 percent (p<0.01) increase in the firm's outlicensing activity, the elasticity increases to 6.7 percent (p<0.01) when *industry asset cospecialization$_k$* is one standard deviation above its mean. The change in the elasticities is significant at the 1% significance level, lending support for Proposition 3.

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Insert Table 2, 3 Here
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Robustness

We perform various robustness checks to validate our findings. The results of these alternative regressions are shown in Tables 4, 5, 6, and 7. First, to ensure that our results are robust to alternative estimation models, we run the regression with population-averaged Poisson, conditional fixed-effects Poisson, and random-effects Poisson models (Model 1-9 of Table 4). These specifications represent three different ways to control for unobserved firm- and industry-specific differences in out-licensing. Among them, the regression coefficients from the population-averaged model provide information about the average response across firms ("population-averaged") rather than about how one firm's response changes with the covariates. The random-effects (RE) specification assumes that the existence of unobserved heterogeneity for firm *i* in industry *k* is random and uncorrelated with the explanatory variables. We also estimate the conventional fixed effects Poisson model, where the group variable is firm *i* in industry *k* and the unobserved group-specific effects are conditioned out prior to parameter

estimation. In the latter model the coefficients of time-invariant variables, including the main

effect of *industry absorptive capacity$_k$* and *industry asset cospecialization$_k$*, will not be

estimated. Nevertheless, we can still estimate the coefficient of the interaction of these variables

with a firm's knowledge transfer capability because the latter is time-variant.

Second, to check whether our findings are robust to alternative specifications of the

discount rate for *codevelopment experience*, we used a zero discount rate in models 1-3 of Table

5. In an unreported analysis, we also used a discount rate of 20% instead of the 15% in the

benchmark model. Third, we measured expected absorptive capacity of potential buyers in an

application industry using an alternative measure that varies over time and industries, e.g. the

application industries' average *R&D intensity$_{ikt}$* (Model 4-6 of Table 5). Fourth, models 1-3 of

Table 6 show the results with our data limited to the primary application industry of each firm

(the industry for which a firm had most patents during the sample period) to check if estimates

are influenced by the number of potential application industries considered. The results are

qualitatively unchanged. Finally, Table 7 shows our benchmark model estimated using the

pooled Poisson QMLE model with discrete measures for *industry absorptive capacity* and

industry asset cospecialization. In particular, we defined two dummy variables equal to 1 if an

application industry k's levels of absorptive capacity and asset cospecialization were greater than

their medians and 0 otherwise. In this specification, the elasticities of knowledge transfer that are

interacted with the dummy variables can be directly computed using the coefficient estimates.

Our results remain consistent in all these robustness checks.

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Insert Table 4, 5, 6, and 7 here
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DISCUSSION AND CONCLUSION

The use of markets for technology through arm's length transactions such as licensing has been an important strategy that shapes the boundary of a firm. Previous studies suggest that the use of markets for technology depends on transaction costs (Gans *et al.*, 2002; Pisano, 1990), appropriability concerns such as the strength of IPR (Arora and Ceccagnoli, 2006; Arora and Merges, 2004; Gans *et al.*, 2002; Gans, Hsu, and Stern, 2008; Gans and Stern, 2003; Teece, 1986), or the sunk costs of an alternative strategy -- product market entry (Gans *et al.*, 2002; Gans and Stern, 2003; Pisano, 1990; Teece, 1986).

This study contributes to the prior literature by highlighting an important hurdle of markets for technology, that is, the need for buyers to further adapt and integrate an external technology to their specific product market. This requires a fuller consideration of the demand-side of the market, and particularly, the consideration of buyers' costs of integrating external technologies. We thus view licensing as a bargaining problem in which both the inventing firm and a potential buyer take into account the integration costs along with other known factors such as transaction costs, entry costs, and appropriability, when determining whether to reach the licensing agreement. We further contribute to the literature by pointing out two demand-side factors of the integration costs -- the buyer's absorptive capacity and the cospecialization among R&D and downstream activities that may be required to commercialize technology.

This study also highlights the importance of firm capabilities in determining the use of markets for technology, particularly the supplier's capability to transferring knowledge and buyer's ability to absorb knowledge. We first show 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 buyer's value chain. All else equal, the typical buyer is more likely to adopt and

license the technology from a seller that has a higher knowledge transfer capability. Second, we argue the cost of integrating the technology to an industry's applications is lowered by the potential buyers' absorptive capacity. Thus, industries where a typical buyer has a higher absorptive capacity are more likely to adopt and license the supplier's technology, and their licensing is less likely to depend on the supplier's knowledge transfer capability. Consistent with these ideas, our analyses --based on a representative sample of technology suppliers-- find that the supplier's knowledge transfer capability, developed over time through codevelopment alliances with other organizations, increases outlicensing. But, we also find the importance of this capability is reduced when potential buyers have strong absorptive capacity.

A shift in focus onto the 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 a small firm cost of entering the market and thus its incentives to out-license. We extend their work by suggesting 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 the 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 productive in knowledge transfer across firm boundaries, a higher cospecialization may reduce buyers' incentive to in-license. In other words, the interaction of suppliers' strong knowledge transfer capabilities and the cospecialization between upstream R&D and downstream activities increases the probability that a licensing deal

takes place. Consistent with this idea, our empirical analyses find that the supplier's knowledge transfer capabilities are especially important when commercialization within buyers involves high cospecialization between their R&D and downstream assets.

Taken together, our findings contribute to strategic management by deepening the understanding of the relationships between firm capabilities and markets for technology. This is consistent with a recent increasing emphasis on considering the role of capabilities in firms' boundary choices (Argyres, 1996; Ceccagnoli *et al.*, 2010; Jacobides and Hitt, 2005; Leiblein and Miller, 2003; Mayer and Salomon, 2006; Parmigiani and Mitchell, 2009; Qian, Agarwal, and Hoetker, 2010).

We would also like to point a major limitation of our study. 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. Gans et al. (2002), however, show that inclusion of the possibility of mergers or acquisition by incumbents of the technology supplier does not alter the effect of considered explanatory variables such as strength of IPR or costs of acquiring complementary assets on the relative attractiveness of competition versus licensing. In other words, these authors implicitly suggest the biases introduced by only considering the licensing choice when studying the forward integration decision of a small technology startup, as in our case, are likely to be small. Nevertheless, we believe that expanding the choice set for commercializing technology is an important and relatively unexplored line of research in the markets for technology literature, especially from the point of view of understanding the optimal technology commercialization mode conditional on cooperation.

Our study provides practical managerial guidance for small firms with a sustained record of inventiveness but limited downstream capabilities. There are numerous examples of such firms: specialist engineering firms in the second half of the 20th century designing chemical plants and related engineering services for large firms; fabless semiconductor firms designing the software for the functioning of semiconductor chips; biotech start-ups specializing in drug discovery for large pharmaceutical companies (Arora *et al.*, 2001). In these small, innovative firms, licensing is often a vital component of corporate strategy. Our study suggests that managers of these firms need to recognize circumstances where they may face a challenge from the buyers in the market for technology, and, more importantly, what factors may mitigate buyers' incentives to acquire external technology, in order to reach a successful licensing deal. For instance, managers of these firms should pay sufficient attention to their potential buyers' ability to integrate external inventions to their specific needs. The lack of this ability would indicate that the innovating firms' capability in knowledge transfer and technical assistance will be especially important for licensing. Additionally, managers of innovating firms need to know their knowledge transfer capability will be especially important if commercialization by potential buyers' require proximate, tight, and frequent communication links between R&D and marketing and manufacturing activities. Similarly, our study suggests that managers of established firms should look for licensors with a strong knowledge transfer capability that is 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 add critical value to their buyers.

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Table 1. 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 sales$_{kt}$	0.00	0.00	-0.21	-0.09	0.06	0.32	-0.06	0.19	-0.06	-0		
12	Industry capital intensity$_{kt}$	0.06	0.13	0.31	-0.27	0.17	0.07	0.03	0.13	-0.06	0.014	-0.18	
	Mean	0.01	0.07	0.13	0.45	12	0.13	0.33	0.42	22.73	0.06	80.91	217949.00
	Standard Deviation	0.14	0.41	0.02	0.08	18	0.24	1.59	0.49	22.80	0	73.67	236512.70
	Min	0	0	0.07	0.16667	0	0	0	0	0	0	20.64	429.55
	Max	8	14	0	0.76	456	1	49.04	1	147	1	458.46	2970184.00

Notes:
1) N=12845
2) All US dollars are all in real terms deflated by the corresponding year's GDP deflator with the base year in 2005.

Table 2. Benchmark Models: Pooled Poisson Estimation

	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$_{ikt}$	0.91	0.93	0.93*
	(0.73)	*(0.73)*	*(0.73)*
Industry capital intensity$_{ikt}$	-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.	12845	12845	12845
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. Marginal 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)*

Table 4. Robustness analyses with alternative estimation methods

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	(Population average Poisson)			(Poisson fixed-effects)			(Poisson random-effects)		
Codevelopment experience$_{ikt}$	0.80**	-25.03***	-14.93***	0.81**	-17.84**	-7.93	0.81***	-22.03*	-10.98
	(0.39)	(8.19)	(6.00)	(0.39)	(10.34)	(6.83)	(0.32)	(14.63)	(8.76)
Industry absorptive capacity$_k$		1.86**					1.70	1.69	1.67
		(1.10)					(1.43)	(1.45)	(1.43)
Industry asset cospecialization$_k$	-0.47	-0.20	-0.95				-0.17	-0.15	-0.46
	(3.86)	(3.86)	(3.86)				(6.48)	(6.44)	(6.49)
Patents$_{ikt}$	0.26*	0.26*	0.25*	0.34	0.32	0.32	0.30	0.28	0.28
	(0.20)	(0.19)	(0.19)	(0.30)	(0.29)	(0.29)	(0.24)	(0.24)	(0.24)
References to Science$_{ikt}$	-0.92**	-0.85*	-0.84*	-0.69	-0.64	-0.65	-0.74*	-0.68	-0.68
	(0.56)	(0.57)	(0.57)	(0.59)	(0.59)	(0.59)	(0.57)	(0.57)	(0.57)
Trademarks$_{ikt}$	-0.59**	-0.61**	-0.61**	-0.72**	-0.64**	-0.66**	-0.66**	-0.64**	-0.64**
	(0.35)	(0.35)	(0.35)	(0.33)	(0.33)	(0.33)	(0.35)	(0.35)	(0.35)
Public$_{it}$	0.59*	0.58*	0.56*				0.67	0.65	0.64
	(0.41)	(0.41)	(0.41)				(12.78)	(12.80)	(12.77)
Firm age$_{it}$	1.97***	1.95***	1.94***	3.15**	3.19**	3.17**	2.39***	2.36***	2.36***
	(0.78)	(0.79)	(0.78)	(1.47)	(1.48)	(1.47)	(0.91)	(0.91)	(0.91)
Exit$_{it}$	-0.81*	-0.81*	-0.81*	-0.62	-0.63	-0.63	-0.77	-0.78	-0.78
	(0.58)	(0.58)	(0.58)	(0.66)	(0.66)	(0.66)	(0.67)	(0.67)	(0.67)
Industry sales$_{kt}$	0.92	0.94*	0.94*	0.91	0.89	0.85	0.81	0.81	0.81
	(0.73)	(0.73)	(0.73)	(1.65)	(1.71)	(1.71)	(1.00)	(1.00)	(1.00)
Industry capital intensity$_{kt}$	-0.54	-0.73	-0.76	-1.26	-1.66	-1.68	-0.89	-1.17	-1.18
	(0.99)	(0.99)	(1.00)	(1.91)	(2.13)	(2.18)	(1.22)	(1.24)	(1.24)
Constant	-10.42**	-10.51***	-10.55***				-10.95**	-11.05**	-11.02**
	(4.53)	(4.48)	(4.39)				(5.10)	(5.11)	(5.09)
Codevelopment experience$_{ikt}$ X industry absorptive capacity$_k$		-14.05***			-10.14**			-12.41*	
		(4.42)			(5.58)			(7.95)	
Codevelopment experience$_{ikt}$ X industry asset cospecialization$_k$			49.75***			27.62*			37.23*
			(18.86)			(21.42)			(27.67)
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.	12845	12845	12845	723	723	723	12845	12845	12845
Log likelihood	n.a.	n.a.	n.a.	-206.12	-205.34	-205.61	-441.80	-440.52	-440.84

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 5. Robustness analyses with alternative measures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(Discount factor=0 for *codevelopment experience*)			(replace industry absorptive capacity with *R&D intensity*)		
Codevelopment experience$_{ikt}$	0.76**	-15.83*	-9.88*	0.79**	2.81**	-11.91**
	(0.39)	(10.22)	(6.51)	(0.40)	(1.55)	(5.23)
Industry absorptive capacity$_k$	1.75**	1.65*	1.79**			
	(1.02)	(1.10)	(1.05)			
R&D intensity$_{kt}$				3.83	9.15	2.58
				(10.13)	(10.76)	(10.54)
Industry asset cospecialization$_k$	-0.17	-0.36	-0.24	-0.25	0.11	-0.74
	(3.96)	(3.87)	(3.88)	(3.09)	(3.06)	(3.09)
Patents$_{ikt}$	0.23	0.23	0.23	0.23	0.25	0.22
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
References to Science$_{ikt}$	-0.84*	-0.79*	-0.79*	-0.93*	-0.99**	-0.88*
	(0.53)	(0.54)	(0.54)	(0.56)	(0.57)	(0.57)
Trademarks$_{ikt}$	-0.65**	-0.67**	-0.67**	-0.59*	-0.55*	-0.60*
	(0.37)	(0.38)	(0.38)	(0.37)	(0.38)	(0.37)
Public$_{it}$	0.69*	0.68*	0.67*	0.53*	0.34	0.49
	(0.42)	(0.43)	(0.43)	(0.40)	(0.44)	(0.40)
Firm age$_{it}$	1.90***	1.87***	1.86***	1.93***	1.85**	1.88***
	(0.78)	(0.78)	(0.79)	(0.78)	(0.80)	(0.79)
Exit$_{it}$	-0.83*	-0.82*	-0.81*	-0.85*	-0.89*	-0.85*
	(0.60)	(0.60)	(0.60)	(0.60)	(0.59)	(0.60)
Industry sales$_{kt}$	0.74	0.82	0.85			
	(0.74)	(0.76)	(0.76)			
Industry capital intensity$_{kt}$	-0.31	-0.41	-0.45	-1.68*	-1.96**	-1.89**
	(0.99)	(0.99)	(0.99)	(1.09)	(1.18)	(1.14)
Constant	-11.82***	-11.97***	-11.85***	-4.36**	-4.41**	-4.15**
	(4.73)	(4.70)	(4.60)	(2.09)	(2.08)	(2.02)
Codevelopment experience$_{ikt}$ X industry absorptive capacity$_k$		-9.03* (5.55)				
Codevelopment experience$_{ikt}$ X R&D intensity$_{kt}$					-12.89* (9.77)	
Codevelopment experience$_{ikt}$ X industry asset cospecialization$_k$			33.68* (20.49)			*40.21*** (16.38)*
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Number of obs.	12845	12845	12845	12845	12845	12845
Log likelihood	-461.65	-460.85	-460.84	-460.20	-459.07	-459.03

Robust standard errors clustered at the firm-application industry level in parentheses

We dropped 'industry sales' from model 4-6 because highly collinear with 'industry absorptive capacity,' which in these models is measured as industry R&D over industry sales.

 *** 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 6. Robustness analyses with only the primary application industry for each firm

	Model 1	Model 2	Model 3
Codevelopment experience$_{it}$	0.79**	-26.50***	-13.37**
	(0.43)	*(9.41)*	*(5.94)*
Industry absorptive capacity$_i$	0.98	1.07	0.94
	(1.28)	*(1.36)*	*(1.30)*
Industry asset cospecialization$_i$	1.00	1.30	0.38
	(5.54)	*(5.61)*	*(5.48)*
Patents$_{it}$	0.15	0.15	0.13
	(0.23)	*(0.23)*	*(0.23)*
References to Science$_{it}$	-1.04*	-0.96*	-0.95*
	(0.68)	*(0.68)*	*(0.68)*
Trademarks$_{it}$	-0.82**	-0.84**	-0.84**
	(0.39)	*(0.39)*	*(0.39)*
Public$_{it}$	0.48	0.45	0.43
	(0.48)	*(0.48)*	*(0.48)*
Firm age$_{it}$	2.45***	2.42***	2.44***
	(0.88)	*(0.88)*	*(0.88)*
Exit$_{it}$	-0.95	-0.96*	-0.95*
	(0.74)	*(0.74)*	*(0.74)*
Industry sales$_{it}$	1.15	1.31*	1.36*
	(0.96)	*(0.99)*	*(1.03)*
Industry capital intensity$_{it}$	-0.42	-0.51	-0.47
	(1.25)	*(1.25)*	*(1.26)*
Constant	-12.30**	-12.86**	-13.04**
	(7.25)	*(7.12)*	*(7.10)*
Codevelopment experience$_{it}$ X industry absorptive capacity$_i$		-14.85*** *(5.07)*	
Codevelopment experience$_{it}$ X industry asset cospecialization$_i$			44.79*** *(18.60)*
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)	(Yes)	(Yes)
Number of obs.	5523	5523	5523
Log likelihood	-349.60	-348.11	-348.41

- Number of firms=506. Thirteen firms are dropped from estimation because their primary application industries happen to be those for which we do not have industry-specific data (USPTO sequence=56).

-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 7. Robustness analyses with dummy variables as moderators

	Model 1	Model 2
Codevelopment experience$_{ikt}$	4.04**	0.78**
	(2.02)	*(0.38)*
Industry absorptive capacity$_k$		1.56*
		(1.16)
Industry absorptive capacity dummy$_k$ ^	0.42	
	(0.38)	
Industry asset cospecialization$_k$	-2.71	
	(4.20)	
Industry asset cospecialization dummy$_k$ ^		-0.13
		(0.41)
Patents$_{ikt}$	0.27*	0.27*
	(0.20)	*(0.20)*
References to Science$_{ikt}$	-0.97**	-0.95**
	(0.57)	*(0.56)*
Trademarks$_{ikt}$	-0.57*	-0.59**
	(0.36)	*(0.36)*
Public$_{it}$	0.57*	0.57*
	(0.41)	*(0.41)*
Firm age$_{it}$	1.96***	1.89***
	(0.79)	*(0.78)*
Exit$_{it}$	-0.85*	-0.84*
	(0.60)	*(0.60)*
Industry sales$_{kt}$	0.93*	0.89
	(0.71)	*(0.75)*
Industry capital intensity$_{kt}$	-0.50	-0.57
	(0.98)	*(1.04)*
Constant	-3.87*	0.92**
	(2.44)	*(0.48)*
Codevelopment experience$_{ikt}$ X industry absorptive capacity dummy$_k$	-3.26* *(2.07)*	
Codevelopment experience$_{ikt}$ X industry asset cospecialization dummy$_k$		4.44*** *(1.50)*
Year dummies (1997-2007)	(Yes)	(Yes)
Firm-application industry fixed effects†	(Yes)	(Yes)
Number of obs.	12845	12845
Log likelihood	-459.00	-458.23

-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.
^: Dummy set to one if the corresponding continuous variable is above its median and zero otherwise.

USPTO sequence codes and application industries	Number of sample firms	Corresponding SIC
1 FOOD AND KINDRED PRODUCTS	5	20
2 TEXTILE MILL PRODUCTS	9	22
3 CHEMICALS AND ALLIED PRODUCTS		28
4 Chemicals, except drugs and medicines	1	281,282,284-289
5 Basic industrial inorganic and organic chemistry	0	281,286
6 Industrial inorganic chemistry	6	281
7 Industrial organic chemistry	62	286
8 Plastics materials and synthetic resins	10	282
9 Agricultural chemicals	67	287
10 All other chemicals	0	284,285,289
11 Soaps, detergents, cleaners, perfumes, cosmetics and toiletries	2	284
12 Paints, varnishes, lacquers, enamels, and allied products	5	285
13 Miscellaneous chemical products	5	289
14 Drugs and medicines	124	283
15 PETROLEUM AND NATURAL GAS EXTRACTION AND REFINING	3	13,29
16 RUBBER AND MISCELLANEOUS PLASTICS PRODUCTS	57	30
17 STONE, CLAY, GLASS AND CONCRETE PRODUCTS	22	32
18 PRIMARY METALS		33,3462,3463
19 Primary ferrous products	2	331,332,3399,3462
20 Primary and secondary non-ferrous metals	1	333-336,339(except 3399),3463
21 FABRICATED METAL PRODUCTS	82	34(except 3462,3463,348)
22 MACHINERY, EXCEPT ELECTRICAL		35
23 Engines and turbines	8	351
24 Farm and garden machinery and equipment	9	352
25 Construction, mining and material handling machinery and equipment	20	353
26 Metal working machinery and equipment	10	354
27 Office computing and accounting machines	66	357
28 Other machinery, except electrical	0	355,356,358,359
29 Special industry machinery, except metal working	35	355
30 General industrial machinery and equipment	54	356
31 Refrigeration and service industry machinery	31	358
32 Miscellaneous machinery, except electrical	4	359
33 ELECTRICAL AND ELECTRONIC MACHINERY, EQUIPMENT AND SUPPLIES		36,3825
34 Electrical equipment, except communications equipment	0	361-364,369,3825
35 Electrical transmission and distribution equipment	23	361,3825
36 Electrical industrial apparatus	19	362
37 Other electrical machinery, equipment and supplies	0	363,364,369
38 Household appliances	15	363
39 Electrical lighting and wiring equipment	11	364
40 Miscellaneous electrical machinery, equipment and supplies	19	369
41 Communications equipment and electronic components	0	365-367
42 Radio and television receiving equipment except communication types	14	365
43 Electronic components and accessories and communications equipment	157	366-367
44 TRANSPORTATION EQUIPMENT		37,348
45 Motor vehicles and other transportation equipment, except aircraft	0	348,371,373-376,379
46 Motor vehicles and other motor vehicle equipment	14	371
47 Guided missiles and space vehicles and parts	0	376
48 Other transportation equipment	0	373-375,379(except 3795)
49 Ship and boat building and repairing	0	373
50 Railroad equipment	1	374
51 Motorcycles, bicycles, and parts	0	375
52 Miscellaneous transportation equipment	0	379(except 3795)
53 Ordinance except missiles	1	348,3795
54 Aircraft and parts	9	372
55 PROFESSIONAL AND SCIENTIFIC INSTRUMENTS	195	38(except 3825)
56 ALL OTHER SIC'S	0	99

Note: An excerpt of the concordance is available at http://www.uspto.gov/go/taf/brochure.htm.