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Licensing speed: Its determinants and payoffs

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ABSTRACT

There has been much research interest in the speed of innovation, although few consistent findings have emerged. In this study, we unpack the innovation process and focus on the commercialization stage to examine two questions: Which licensor and patent characteristics determine the speed of licensing? How does the speed of licensing impact the royalties and lump-sum payments to licensors? We addressed these questions by proposing that licensing speed is influenced by variables for licensor prominence (*size* and *experience*), licensor knowledge structuration (*technological depth*, *technological breadth* and *experience*), and patent appeal (*forward citations*, *scope* and *complexity*). We predict and find that these variables work to increase the size, complexity and duration of the licensing-out task, while also allowing licensors to take their time to review, negotiate and select agreements with higher royalty rates. These findings are counter to arguments for a fast-paced innovation strategy, as it suggests that for the commercialization stage of the innovation process the relationship between licensing speed and licensor royalty rates rewards a 'less haste, greater payoff approach.

1. Introduction

Innovation speed is considered an important organizational attribute that impacts firm performance (Kessler and Chakrabarti, 1996). Fast innovators have been found to have greater revenue returns (Ringel et al., 2015), more new product development (Acur et al., 2010), and growth in sales and initial public offerings (Eisenhardt, 1989). However, some scholars offer an alternative view showing that the fast innovation sometimes has disadvantages. For example, fast innovation is less likely to produce impactful and profitable outcomes (Steen and Dhondt, 2010) and has hidden costs linked to the mistakes and inefficiencies that come with innovating quickly (Crawford, 1992). To resolve this conflict and better understand the determinants and impact of innovation speed, we follow calls to unpack the innovation process for more nuanced, context specific examinations (Carbonell and Rodríguez-Escudero, 2009; Chen et al., 2005; Langerak and Hultink, 2008). Up to now, research on innovation speed has focused on the speed across all three stages of the innovation process: the conception of an idea, the development that idea, and the eventual commercialization of that idea (Kessler and Chakrabarti, 1996). In this study, we focus on the speed of one stage of the innovation process: commercialization and, in particular, the activity of technology licensing. We explore the determinants and impact of licensing speed, defined as the length of time between patent application and announcement of a licensing agreement.

Examining licensing speed is worthwhile for two reasons. First, licensing is an increasingly important method of innovation commercialization. There is a growing market for owners of patented technologies (i.e., licensors) to grant a license to others (i.e., licensees) to use, modify, and/or resell the patented technology in exchange for compensation (Athreye and Cantwell, 2007). Within just the U.S., it is estimated that the annual value of licensed technologies has increased from $50 billion in 1997 to $138 billion in 2014 (Moyer, 2016).

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Second, time is a central yet relatively unexamined aspect of licensing. As patented technologies are protected for a finite time period (e.g., in the U.S. and Europe it is 20 years from the filing date of the application), some studies have examined the duration and timing of the patent application, approval process and renewal fees (Popp et al., 2003; Dechenaux et al., 2003; Drivas et al., 2016; Gans et al., 2008). However, surprisingly little attention has been paid to licensing speed and its effects on licensing payments to the licensor. Similar to the research on innovation speed, the few studies that do consider the pace of licensing, the results are inconsistent. On the one hand, the view is that the longer it takes a licensor to license its patented technology, the greater the reduction in the protected time period for monopoly profits, which reduces the value of the technology to both licensor and licensee (Hegde, 2014; Markman et al., 2005). On the other hand, while fast licensing might result in returns sooner, this could be at the risk of a hurried sub-optimal deal and lower price that results in reduced returns overall (Allain et al., 2011; Mauleon et al., 2013).

One explanation for this counter view about the benefits of licensing slowly is that innovation commercialization involves ambiguous search effectiveness, uncertain IP rights, and difficult to predict valuations of the technology (Gans et al., 2008; Zeckhauser, 1996). As such conditions are also likely to affect the ability of potential licensing partners to locate and contract with one another (Elfenbein and Elfenbein, 2007), we suggest they would reward a careful and judicious approaching to technology licensing. In other words, hasty licensing could negatively impact both the initial lump-sum payments and the longer-term revenues from royalties linked to future use and sales of the technology. We suggest that an analysis of the licensor and patent characteristics can explain this inconsistency in how licensing speed impacts licensor payoffs.[1] This will help scholars and managers to better understand how the speed of one aspect of the innovation process (licensing), can help a variety of organizations (e.g., technology firms, universities, and patent assertion entities) to profit from their intellectual property.

We present and test a model based on the premise that licensor prominence (relative standing or status), licensor knowledge structuration (knowledge portfolio depth and breadth), and patent desirability increase the time it takes to reach a licensing agreement. These licensor and patent factors work to increase licensor visibility, standing, and expertise. This, in turn, provides licensors with an abundance of potential licensees that increases the size of the licensing-out task. It also provides confers licensors with a position whereby they take their time to review and negotiate the options to attain the most attractive payoff in terms of royalty rate or lump-sum payment. We present and test hypotheses based on this theoretical premise.

The empirical setting for our study is the U.S. biopharmaceutical industry. It is an industry with a growing market for technology licensing (Wuyts and Dutta, 2008; Schweizer, 2005) and one that is shaped by licensing and other forms of technology transfer (Shin and Lee, 2013). We examine the speed of biopharmaceutical patents leading to licensing agreements during the period 1993–2008, inclusive, of which 117 were licensed while 34,543 were willing to be licensed but ultimately were not. The results indicate that variables that reflect licensor prominence and licensor knowledge structuration act to increase the time it takes to reach agreements. We find that characteristics of the patent itself which reflect desirability such as forward citations and scope increase licensing time, while patent claims, surprisingly, reduce licensing time. Slower licensing speeds for those patents that were ultimately licensed result in higher royalty rates to the licensor.

2. Theory and hypotheses

Licensing is a transaction between two parties: a licensee and a licensor. The licensor owns the intellectual property (IP) and seeks to extract value from it in the form of licensing revenues or through agreements that provide access to other technologies or new markets (see: Shapiro, 1985). Licensors may also license-out their IP because they lack the financial, physical or intellectual resources to commercialize it (Gambardella et al., 2007) or to help reduce the incentives for other firms to develop competing IP (Gallini, 1984). Licensees, on the other hand, typically acquire patented technologies as a means of updating or diversifying their technological assets (i.e., as a form of R&D outsourcing). It is considered to be an important organizational learning activity (Pitkethly, 2001). Licensing-in can also be a protective strategy, whereby licensees acquire but do not commercialize technologies simply to thwart competitors accessing them (Cohen et al., 2000). These are some of the key strategic reasons that motivate licensors and licensees to license and will likely impact the time it takes to reach a licensing agreement.

Drawing upon the learning, alliance and innovation research literatures, we hypothesize how two licensor factors (licensor prominence and licensor knowledge structuration) and characteristics of the patent itself contribute to licensing speed and licensor payoffs (see Fig. 1). Licensor prominence is the extent to which licensors will be known to and attract licensees. A licensor's knowledge structuration is the breadth and depth of its technological knowledge portfolio (George et al., 2008). Our fundamental premise is that strength in both prominence and knowledge structuration increase licensor visibility, standing, appeal and expertise. This increases the number of possible licensees interested in a licensor's technology, which increases the size, complexity and duration of the licensing-out task. Furthermore, strength in prominence and knowledge structuration confer a ‘seller's market’ position and greater bargaining power on the licensor. Thus, in addition to drawing many possible licensing opportunities, prominent licensors are disposed to prudently review and wait for the most attractive offer.

In addition to licensor prominence and knowledge structuration, we also consider patent appeal. The more cited, the more complex and the broader a patent, the greater the interest from licensees because of the potential value associated with such characteristics. These effects all work to increase the size and duration of the licensing-out task, the licensor bargaining position, and the potential payoffs.

[1] When we refer to licensor “payoffs”, we examine royalty rates and lump-sums paid to licensors. We cannot make inference about the final payment made to licensors which is ultimately linked to sales.

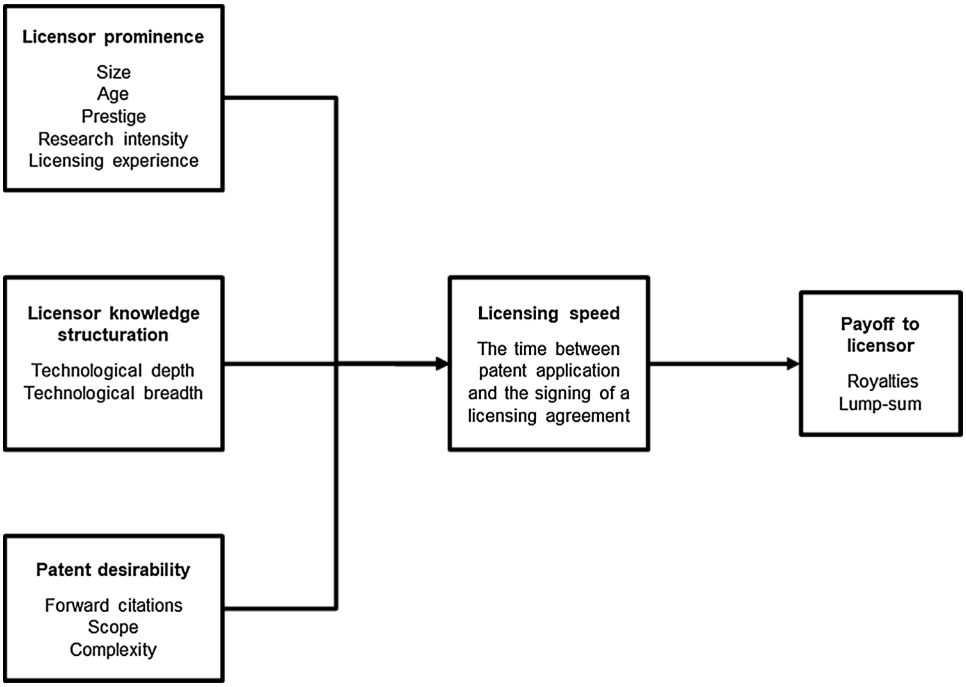

Fig. 1. Theoretical model.

2.1. Licensor prominence

We define licensor prominence as a licensor's standing or status relative to other licensors, as perceived by potential licensees. It is a signal of the latent value of a licensor's patent technology offerings, which impacts licensing speed through different kinds of visibility, appeal and power effects.

We argue that prominent licensors take their time to reach a licensing agreement because they are in a similar situation to the phenomenon of 'superstar' employees in industries such as entertainment and academia (Rosen, 1981) and 'star scientist' employees in the biotechnology industry (Zucker and Darby, 1996). Studies suggest that as these star employees are in high demand, they are very protective of their knowledge and are fussy about who they collaborate with. Similarly, prominent licensors will attract licensing-out options and thus be less inclined to rush a licensing agreement. They are in a position to carefully and methodically choose the licensee whom they believe will generate the best payoff. They may even take extra time to allow for offers to be sequentially renegotiated among potential licensees, as the terms become increasingly favorable.

Research suggests that licensees could perceive licensor prominence in terms characteristics such as organizational age and size which attracts third parties, such as investors, customers and suppliers (Rindova et al., 2005; Shrum and Wuthnow, 1988). Ultimately, the conferred legitimacy makes organizations more prominent in their markets (Deephouse, 2000; Rao, 1994). Thus, being big and established helps make licensors known to licensees, which helps to attract more licensees which leads to an increase in the size, complexity and duration of a licensor's licensing-out task. Furthermore, large licensors would be less desperate for quick licensing payoffs as they are more likely to own the assets necessary develop their own patented technologies (Teece, 1977), which motivates them to not rush into a licensing agreement. Equally, small and young licensors will be more desperate for licensing deals that provide financial income (Forbes, 2005) and less likely to own the complementary assets needed to develop the technology (Kollmer and Dowling, 2004; Gambardella et al., 2007), in turn motivating them to more hastily seek a licensing agreement.

It is also important to note while bigger licensors will likely have greater resources allowing for quicker partner search and identification (Ndofor and Levitas, 2004), in general, smaller firms tend to be faster and more responsive than larger firms (Chen and Hambrick, 1995). We suggest that large licensors, like large firms in general, will suffer from significant levels of formality and bureaucracy that can delay the decision-making proves that is central to reaching a licensing agreement (Baum and Wally, 2003; Grinyer and Yasal-Ardekanl, 1981; Judge and Miller, 1991).

Hypothesis 1a. Licensor age increases the time it takes to reach a licensing agreement.

Hypothesis 1b. Licensor size increases the time it takes to reach a licensing agreement.

Licensor prestige is the extent to which licensors have a reputation for high-quality patents that helps them be discovered by potential licensees. Prestige works in two ways to impact licensor prominence and the time it takes to reach agreement. First, licensors that are prestigious in terms of quality of patent stock will have a 'halo' that attracts more licensees (Sine et al., 2003). For example, research has found that institutional prestige increases a university's licensing rate as the ability to license inventions is largely influenced by the quality of current and past inventions (Sine et al., 2003). Second, strong prestige enhances the visibility of a licensor, thereby increasing the likelihood that potential licenses will be more aware of the licensor (Granovetter, 1985). So, in the same way a scientist's prestige influences the extent that scientist was followed, read and cited (Merton, 1968), we argue that the same logic would apply to prestigious licensors. Like star scientists, prestigious licensors would use their standing to be highly selective in their collaborations and technology transfer partnerships. They would be more careful, and if inclined slower, in deciding with whom they share their time and technology. This diligence is important due to the risks of asset specificity, opportunity costs and appropriability that come with licensing-out many technologies (Fosfuri, 2006).

Hypothesis 1c. Licensor prestige increases the time it takes to reach a licensing agreement.

Our fourth and fifth licensor variables are research intensity and licensing experience. Research intensity is the degree to which a firm engages in internal research activities (Schildt et al., 2012). When licensors have a high research intensity, they will more likely produce, patent, and license IP (Arora and Ceccagnoli, 2006). The amount of internal R&D is also expected to promote collaboration and influence a licensor's potential to discover or be discovered by licensees (Zhang and Baden-Fuller, 2010; Kani and Motohashi, 2012). Licensing experience also enhances licensor standing. It makes them more known in the technology market place and better able to promote their technology (Aggarwal and Hsu, 2009; Anand and Khanna, 2000). Accordingly, we suggest that research intensity and experience enhance licensor prominence through activity, bestowing licensors with a greater visibility and choice of licensees, thus resulting in slower licensing.

Hypothesis 1d. Licensor research intensity increases the time it takes to reach a licensing agreement.

Hypothesis 1e. Licensor experience increases the time it takes to reach a licensing agreement.

2.2. Licensor knowledge structuration

Knowledge structuration is the extent to which a licensor's knowledge portfolio is based on multiple or a few technology domains (George et al., 2008). Knowledge structuration indicates a licensor's the breadth and depth of technological expertise, which is linked to learning and exploration capabilities (e.g., Ahuja and Morris Lampert, 2001; Rosenkopf and Nerkar, 2001). A licensor strong in technological depth has at least one area of knowledge specialization (Ruckman and McCarthy, 2017). Such narrow expertise is positively linked to knowledge transfer in general, as well as licensing agreements (Arora and Gambardella, 1990), within the same domain of expertise. Licensees are more likely to find and want to partner with licensors who have strong technological depth in a matching or complementary area (Ahuja, 2000). This is especially the case in the biopharmaceutical industry, where innovation revolves around specific areas of scientific expertise (Henderson and Cockburn, 1994).

Licensor technological breadth is the variety or scope of technological knowledge areas a firm has explored (Ruckman and McCarthy, 2017). It is the degree to which licensors have previously sought out and used new knowledge, and is an indicator how open and responsive they are to consider new solutions and partnerships in the future (Laursen et al., 2010; Katila and Ahuja, 2002). Breadth helps licensors to not only find or attract licensees from a variety of technological areas, but also provides the licensor with the knowledge to recognize the potential value of these varied licensing opportunities. For example, Ceccagnoli and Jiang (2013) found that licensors with strong technological breadth can more expertly and meticulously review different potential licensing opportunities.

Based on these technological depth and breadth arguments we propose that licensors with strong technological depth and strong technological breadth, like the other variables in our model, helps licensors discover and be discovered by licensees who are in similar technological areas. This increases the size and duration of the licensing-out task and enhances the licensor bargaining position to diligently reach an agreement.

Hypothesis 2a. Licensor technological depth increases the time it takes to reach a licensing agreement.

Hypothesis 2b. Licensor technological breadth increases the time it takes to reach a licensing agreement.

2.3. Patent desirability

Forward citations reflect the knowledge impact of a patent (Duguet and MacGarvie, 2005), and are an indicator of the value and desirability of the patent (Ceccagnoli et al., 2010; Harhoff et al., 2003; Lanjouw and Schankerman, 2004). Patent *scope* refers to the breadth of technological areas cited by the patent's technology (Ruckman and McCarthy, 2017; Sakakibara, 2010). It can be interpreted as a measure of the generality of knowledge and is linked to licensing likelihood (Gambardella et al., 2007). Patent *complexity* is the number of technological claims made by the patent (Palomeras, 2007; Sakakibara, 2010). Claims specify the components or building blocks of a patented invention, and they are indicative of the purview of the invention (Hall et al., 2001). The greater the claims, the more widely applicable, the more commercially exploitable and the more desirable the patent is likely to be (Soranzo et al., 2016). Thus, for licensing speed, the greater a patent's forward citations, scope and complexity, the more licensees it will attract, increasing the duration of the licensing out-task, while also conferring the licensor with the position and options to be discerning.

Hypothesis 3a. Patent forward citations increase the time it takes to reach a licensing agreement.

Hypothesis 3b. Patent scope increases the time it takes to reach a licensing agreement.

Hypothesis 3c. Patent complexity increases the time it takes to reach a licensing agreement.

2.4. Payoff to Licensors

The payoff to a licensor is typically an up-front lump-sum and/or royalty rate paid as a percentage of the final sales. Sakakibara (2010) found evidence that the relative bargaining power of a licensor and the desirability of a patent influence the total payoff to a licensor. Focusing on patent licensing contracts in Japan, she found that some of the variables (*licensor size*, *licensor research intensity*, *patent scope* and *patent complexity*) that we use in our study, are linked to better payoff outcomes. Furthermore, she found that the royalty rate better represented the price of the licensing contract than did lump-sums.

There are a multitude of studies which justify the presence of royalties as a consequence of the existence of informational asymmetries between licensor and licensee (Gallini and Wright, 1990; Macho-Stadler and Verdier, 1991; Beggs, 1992). Similarly, Mauleon et al. (2013) find that when there is imperfect information about the relative bargaining power of the parties as well as strong interest in the patent, then licensors prefer and benefit more from royalty agreements. Our interest, however, is not which type of payoff will predominate (see: Kamien and Tauman, 1986), but rather whether licensing speed affects the payoffs. Although it was not the focus of her study, Sakakibara (2010) found that slower licensing speeds were associated with lower royalty rates, however, she did not include any of our licensor prominence or licensor knowledge structuration variables. Mauleon et al. (2013) found that the time it takes to reach a licensing agreement is greater whenever the licensor chooses to negotiate up-front fixed fees instead of per-unit royalties. Although both these have a different focus and theoretical lens to ours, they highlight the interest in examining the connection between licensing speed and licensor payoffs. As we have previously argued that there are good reasons to slow down licensing speed (licensor prominence and knowledge structuration leading to more potential licensees), it is a natural extension that licensor payoffs will be higher for those who do actually slow down their licensing speed.

Hypothesis 4. A slower licensing speed increases the payoffs to the licensor.

3. Data and method

3.1. Data setting and sample

Our data are patents[2] in the biopharmaceutical industry, where licensing of patented technologies is prevalent and important to firm performance (Anand and Khanna, 2000; Hagedoorn, 2002). Our sample of licensing agreements includes only exclusive licenses. This ensures that a licensor is not concerned with licensing the same technology to different (i.e., non-exclusive licenses). The agreements were gathered from the RECAP database by Deloitte. RECAP lists the world's biotechnology licensing agreements and alliances and a review of similar biotechnology databases concluded that RECAP's data was relatively comprehensive (Schilling, 2009). Furthermore, it has been used as a source of data in recent studies on organizational alliances (Adegbesan and Higgins, 2011; Yu et al., 2011).

An initial search of non-university[3] licensing agreements involving patents between 1993 and 2008 yielded 297 patents. The RECAP database also provided information about the licensor payoff from the agreement, the past licensing history of the licensor and the patent involved. Accounting data (revenues and R&D expenditures) were gathered using Compustat. The data used to create the patent and the citation-based variables came from National Bureau of Economic Research's U.S. patent citation data file (Hall et al., 2001) or from searches of the U.S. Patent and Trademark Office patent database for data after 2006. After data matching across three databases, the sample was reduced to 117 agreements.[4]

To determine all the patents that were willing to be licensed, we first gathered all the biopharmaceutical patents. We noted the 4-digit International Patent Categories (IPC) of the licensed patents and then gathered all the patents in the National Bureau of Economic Research database in those same categories.[5] There were over 90,000 patents that were granted between 1988 (5 years before first agreement in our dataset) and 2007 in these 18 categories. In total, 54,953 biopharmaceutical patents were retained after those with missing patent owner data were dropped.

[2] The knowledge codified in patents is public knowledge leading to complete information for both licensors and licensees with regards to ascertaining the quality of the technology. However, there still remain information asymmetries inherent to all licensing transactions. The licensor does not know the fit of the technology into the licensee's co-specialized assets (Ceccagnoli et al., 2010) or the will of the licensee to actually develop the technology post-contract (Hegde, 2014). The licensee does not know the intention of the licensor to adequately transfer the knowledge post-contract (Macho-Stadler and Verdier, 1991).

[3] Agreements involving university licensors were not included in the dataset as university technology transfer offices have differing structures with different motivations (Markman et al., 2005) which may not emulate the other profit-driven firms in the sample.

[4] The resulting dataset limits the licensors in terms of company size (very small firms with no financial history are dropped) and patenting history (licensors must have patented at least once).

[5] The 18 IPC categories are: A01N, A61B, A61F, A61K, A61M, A61N, A61P, B05B, C07C, C07D, C07H, C07K, C12N, C12P, C12Q, F21V, G01N, Q61K.

3.2. Model

For the portion of this study that explores the determinants of the speed of a licensing agreement, survival analysis techniques were employed as they model the risk of an event occurring (Arora and Nandkumar, 2009). The choice of which survival analysis specification to use depends on the assumptions about the distribution of risk over time for the event in question. Time 0 is when the technology is filed for a patent in our dataset and Time 1 is when the technology is licensed, bearing in mind that 117 patents are actually licensed among the patents that are willing to be licensed. After a patent has been applied for, the technology gains credibility, as does the firm that owns it, and thus the chances of the patented technology being licensed are expected to increase over time (Gans et al., 2008).[6] However, after a technology has either failed a clinical trial or has become exorbitantly expensive to develop further, the chances of it being licensed decrease. Logically, in between these points of patent application and patent undesirability, there should be a point of maximum probability. The survival analysis specification that appropriately reflects this risk profile is the lognormal model which is an accelerated failure time model:

$$\ln(t_j) = \beta_0 + x_j\beta_x + \mu_j, \tag{1}$$

where t_j is the length of time to the event (licensing agreement) for observation j, x_j is a vector of observation-specific variables, and μ_j is an error term that is normally distributed.

It is important to control for sample selection which may bias the survival analysis results. Sample selection in this context occurs when unobserved factors that influence the licensing speed help determine whether licensing speed is observed at all. When this happens, values of the dependent variable for uncensored observations are systematically unrepresentative of the population being studied (Boehmke et al., 2006). We model both the selection and survival analysis simultaneously[7] using the same independent variables in both processes where the dependent variable in the selection equation is *Willing*. Thus, the survival analysis has two stages: first, the willingness of a patent to be licensed-out and, second, the speed at which willing patents were licensed. Those patents that are willing but not ultimately licensed-out are right-censored.

In a quest to understand the implications of slow or fast licensing agreements, the second part of the empirical section will explore the relationship between licensing speed and licensor payoffs from the agreement itself just for the 117 licensed patents. Sakakibara (2010) examined the determinants of the licensor payoffs (lump-sums and royalty rates) from licensing agreements. Borrowing from Sakakibara (2010), we use three-stage least square (3SLS) regressions to estimate the two equations simultaneously while accounting for possible interdependence between the two dependent variables. This allows for the case of an agreement with both a lump-sum payment and a royalty rate.

As the determinants of licensing speed and licensor payoffs are the same, we have an endogenous system which must be jointly estimated to maintain consistency in the results. The two-equation system is as follows:

$$\begin{aligned} \ln(t_j) &= \beta_1 + x_j\beta_{1x} + Z_j\beta_z + \mu_j, \\ PAYOFFLR_j &= \beta_2 + x_j\beta_{2x} + \beta_t t_j + v_j \end{aligned} \tag{2}$$

where t_j, x_j and u_j are as defined in Eq. (1), Z_j is an instrument for licensing speed, $PAYOFF\_LR_j$ is the payoff from the agreement to the licensor and v_j is a normally distributed error term. Following the three step procedure outlined in Adams et al. (2009) and Angrist and Pischke (2009), we are able to estimate the above system despite the first stage being non-linear, avoiding the trap of the “forbidden regression”. The estimates for licensing speed from the first stage of Eq. (2) are instrumented for itself in an intermediate stage (not shown) and then the estimates from that regression are subsequently substituted for licensing speed in the final stage of Eq. (2).

The consistency of the estimation hinges on the choice of an instrument for licensing speed (Z_j). We consider the instrument: *Average licensing speed*. It is a good candidate for an instrument as it is highly correlated with the current agreement's licensing speed but not highly correlated with the licensor's payoffs from that agreement.[8] Historical firm-level average licensing speeds act as a determinant of the current agreement's licensing speed through efficiencies of repeated licensing activities. Licensing teams learn from previous identification of partners, evaluations of partners and technologies, and negotiations and, despite each agreement having unique aspects, these learning curves will influence the current agreement's licensing speed (Colombo et al., 2006; Ruckman and McCarthy, 2017). Yet historical firm average licensing speeds do not have a direct effect on the current agreement's payoffs to the licensor. A licensor's payoff from a given licensing agreement is uniquely determined by the qualities of the patent itself, characteristics of the licensor and the speed of the agreement. We confirm the strength of the instrument following procedures in Murray (2006). First, the instrument is shown to be positively correlated with the endogenous variable, *Licensing speed*, by its significance in the licensing speed regression. Second, we test for over-identification by calculating the Sargan test of whether the instrument is correlated with the residuals from the main stage ($n^*R^2 = 0.41$, distributed as χ^2 where $\chi^2_{(1)} = 3.84$ for p-value $= 0.05$) and confirm that the instrument is not correlated with the residuals. Together, these two tests indicate that the instrument is valid.

[6] Ideally, we would measure time 0 as the moment the licensor decided to seek a licensee for its patented technology although this was not possible. Instead, we use the accepted fact that the act of applying for a patent is a protective measure which reflects value when we assume is a precursor to a search for licensees.

[7] For a full explanation of the approach, see Boehmke (2005) and for recent examples see Homburg et al. (2014) and Heidl et al. (2014).

[8] This approach is similar to the “friend-of-friend” approach for identifying instruments (Shriver et al., 2013; Zeng and Wei, 2012) which relies on a primary link (between current licensor payoffs and current licensing speed), a secondary link (between current licensing speed and past average licensing speed) and an indirect link (between current licensor payoffs and past average licensing speed). As the indirect link has a degree of separation from the primary link, it is ignored while the secondary link provides a good instrument for the primary link.

3.3. Dependent variables

Willing indicates whether a patent is willing to be licensed-out by its owner. Firms are likely to protect and develop core technologies (Rivera and Kline, 2000), whereas peripheral technologies are more difficult to effectively exploit commercially and, thus, tend to be licensed-out (Gambardella et al., 2007). Palomeras (2007) found evidence that firms are more likely to showcase and promote to licensees their patents that do not fit with its core technology. In addition, when a patent owner's technological depth is high, the benefits of keeping and developing the technology will likely be greater; whereas transferring the technology could negatively impact the patent owner's market (Sakakibara, 2010). As such, we measure our *Willing* variable as 1 if the patent is a core technology for the patent owner and 0 if it is non-core. We use the definition for core used in Vanhaverbeke et al. (2012). All IPC subclasses within the biotechnology classes in which a company had successfully applied for a patent during the previous five years were labeled as "core" patent classes. Sub-classes in which a company received a patent in the year of observation but did not receive a patent in the previous five years were considered "non-core". Since knowledge in these non-core patent classes remains relatively new for the firm immediately after it applied for a patent, these patent classes were considered as "non-core" for a period of three years. This dependent variable is only used in the selection regression.

Licensing speed measures the time from the invention of a technology to its license. As the exact invention date of a technology is extremely difficult to pin-point, we proxy it with the date of the application to the patent office. This act signifies that the technology is potentially valuable and is usually a first step in the process of finding a licensing partner, as patented technologies not only protect the licensor but also provide clear guidelines for the licensee. It is measured as the number of days between the application for a patent and the signing of a licensing agreement for the patented technology. The end date for patents that are willing to be licensed but not ultimately licensed is the end of the study (January 1, 2008).

The payoff from a licensing agreement to a licensor is measured using two variables: *Lump-sum payment* and *Royalty rate*. The *Lump-sum payment* is every pre-commercial payment that could be made by the licensee to the licensor and typically encompasses upfront payments, milestone payments, research spending, equity purchases and options. The *Royalty rate* contains the highest possible rate of returns that will be paid to the licensor from a future commercialized product associated with the technology in the licensing agreement according to the agreement when signed. These two payoffs were used in a recent study of the price of patent licensing (Sakakibara, 2010) and we borrow that empirical technique of looking at the two types of payoffs separately while accounting for the interdependence between the two.

3.4. Licensor variables

Size is measured as the logarithm of organizational revenues. Revenues are a proxy for the number of employees[9] and have been used in research that explores the determinants of technology licensing (Fosfuri, 2006).

A licensor's *Research intensity* is calculated by dividing R&D expenditure by revenues, the same measure that Cohen and Levinthal (1990) used in their study of absorptive capacity. Compared to using absolute R&D spending alone, this approach is considered to provide a more accurate indication of the fraction of resources that a firm allocates to research activity because it adjusts for revenue amount (Lane and Lubatkin, 1998; Schildt et al., 2012).

Prestige is a proxy for the licensor's technological reputation as determined by third parties through forward citations. Forward citations for a patent are correlated with value and importance of the technology (Ceccagnoli et al., 2010; Harhoff et al., 2003; Lanjouw and Schankerman, 2004). A forward citation occurs when another patent acknowledges the original patent as a technology source or pioneer. *Prestige* is measured as the average forward citation among the patents in the firm's patent stock within five years of each patent's grant date (i.e., if the patent was granted in 1999, forward citations would be recorded up to and including 2004). Leone and Reichstein (2012) use a similar measurement for a control variable when determining the speed of licensee post-contractual invention and Kani and Motohashi (2012) use the same measurement as a reflection of the potential demand for a licensor's technology.

Age is the length of time a licensor has been actively researching and reflects the licensor's legitimacy, power and standing. Rothaermel and Boeker (2008) find that older biopharmaceutical firms have a greater chance of alliance participation. It is measured as the difference between the date of incorporation of the patent owner and the date the patent application.

Experience is measured as the number of outward licensing agreements by the patent owner in the five years before the patent application. Kim (2009) and Kim and Vonortas (2006) find that licensor outward licensing experience increases the likelihood of achieving a licensing agreement.

Depth is the number of patents granted to the patent owner in same IPC as the patent during the five years before the patent was granted. This variable indicates the extent of the patent owner's existing knowledge in a particular technological area. Licensors that have a depth of knowledge in a specific area to a licensee will have a technological familiarity (Leone and Reichstein, 2012) or technological proximity (Sakakibara, 2010) that results in greater licensing opportunities (Ahuja, 2000).

Breadth is the technological scope of a firm's past patenting efforts. The broader a firm's patent stock, the more diverse is its own internal research spectrum and the better it is able to convey specific knowledge to third-parties. It is measured as the number of different IPC classes the patent owner patented in during the five years before the patent was granted. This particular measurement of technological breadth follows Zhang and Baden-Fuller (2010) and Leone and Reichstein's (2012) "technological diversity" variable.

[9] A sensitivity analysis for firm size with the number of employees was not possible due to deficiencies in this variable across the observations.

The speed of activities performed in the past has been found to affect the current speed of the same activities (Perlow et al., 2002) and, as such, we account for whether past licensing speed affects a current agreement's licensing speed. *Average licensing speed* is measured as the patent owner's average licensing speed for all outward licensing agreements in the five years before the patent's application.

3.5. Patent variables

The licensed patent's forward citations (*Patent forward citations*) are the references by subsequent patents, owned by other entities, which have built on the patented technology. A large number of forward citations can indicate the magnitude of impact and thus value and appeal of a patent (Rosenkopf and Nerkar, 2001). *Scope* is the number of IPCs listed on the patent (Sakakibara, 2010). The number of IPC classes can be interpreted as a measure of the generality of knowledge (Gambardella et al., 2007). The number of technological claims (*Complexity*) in a patent is a proxy for its complexity and desirability. Claims specify the components or building blocks of a patented invention, and they are considered indicative of the purview of the invention (Hall et al., 2001). The greater the claims, the greater the range of the patent, which increases the likelihood the patent will face legal disputes (Harhoff and Reitzig, 2004). This reduces the attractiveness of a patent which would make it slower to license.

4. Results

Table 1a shows the variable measures and descriptive statistics for all the biopharmaceutical patents and those that are willing to be licensed-out and Table 1b does the same for the 117 licensed patents. The tables indicate the diversity of firm and patent determinants included in the sample. Even though our sample is from one industry, there is considerable range for several of the variables. Table 2a shows the variance inflation factors (VIFs) for the independent variables and the correlations among all the variables for the patents that are willing to be licensed-out. Table 2b shows the same for the patents that were actually licensed-out. As all the VIFs are well below 5, there is no concern with multi-collinearity (Kutner et al., 2004).

The estimations for the duration model in Eq. (1) with the associated selection regressions are presented in Table 3. Columns 1a and 1b include only the licensor variables, Columns 2a and 2b include only the patent variables and Columns 3a and 3b have all variables together (these last columns will be the focus of our discussion). The lognormal specification for the duration model is shown in an accelerated failure-time form, which means that variables with positive estimated coefficients are interpreted as slowing down licensing speed and negative estimated coefficients as accelerating licensing speed.

Although it is not a focus of this study, the selection results are intriguing. The columns with *Willing* as a dependent variable show that patents that are owned by firms that are large and have many forward citations are more likely to be willing to be licensed-out. In contrast, the patents owned by firms that have high prestige, are older, have experience and depth are unlikely to be willing to be licensed out. There are few studies to compare these results to and their results are somewhat inconsistent.[10] Kani and Motohashi (2012) found that larger firms are more likely to be willing to license-out and that prestige is not significant for willingness, while Gambardella et al. (2007) found that patents with large scope are unwilling to be licensed by their owners. Palomeras (2007) found that patents with many forward citations are unlikely to be willing to be licensed-out as they would likely be kept for internal development, although he did not control for non-core patents.

The results in Table 3 indicate a number of significant and positive findings. These support our predictions that strength in licensor prominence, licensor knowledge structuration and patent desirability, all work to slow down the time it takes to licensing-out a patented technology. This provides evidence that strength in these factors endow licensors with an abundance of licensing opportunities that not only increases the size, complexity and duration of the licensing out-task, but allows licensors to take their time to review, negotiate and select the most attractive offer. Specifically, we find agreements with large licensors are signed slowly (Hypothesis 1b). This is consistent with the view that large patent owners are less motivated to license because they have the complementary assets to develop and exploit their technological portfolio (Arora and Fosfuri, 2003; Sakakibara, 2010). Patents owned by licensors that have strong technological *Depth* in the area of the patent (Hypothesis 2a) and strong technological *Breadth* across technological fields within the biopharmaceutical sector (Hypothesis 2b) are found to have slower licensing speed. Thus, strength in both these dimensions of knowledge structuration indicates that licensors are more likely to be known for both their specific and broad technological expertise. Patents with strength in *Forward citations* and *Scope* have slower licensing agreements (Hypotheses 3a and 3b). This was expected as both these variables are considered to be an indicator of patent's knowledge impact (Duguet and MacGarvie, 2005) and applicability, value and desirability (Ceccagnoli et al., 2010; Harhoff et al., 2003; Lanjouw and Schankerman, 2004). Finally, patents that have many claims (*Complexity*) had quicker licensing agreements (Hypothesis 3c). This is surprising as claims are an indicator of patent complexity and uncertainty and thus the likelihood of legal disputes (Harhoff and Reitzig, 2004). Such indicators would make the technology less desirable and slower to transfer. As the number of claims in a patent is linked to the novelty of the technology, and in turn both patent value and expected disputes, it may that licensors are more inclined to do a particularly thorough job of laying out all the specifics of the technology when filing.

[10] Gambardella et al. (2007) and Kani and Motohashi (2012) used survey data to determine willingness while Palomeras (2007) measured willingness by whether a patent was submitted to a website used to solicit licensees.

Table 1a
Statistics of variables, all patents (n = 54,953) and patents willing to be licensed (n = 34,660).

	Variable	Measure		Mean	Std. Dev.	Min	Max
Dependent variables							
1	Willing	1: if patent is non-core, 0 if core (core patents are those that the patent owner has other patents granted in the same IPC sub-sategory within previous 5 years)		0.6	0.5	0	1
2	Licensing speed	Number of days between patent application and license agreement (or end of study for those that were not licensed), for patents where willingness = 1		4196.3	1032.5	55	5840
Patent owner variables							
3	Size	Revenue, $US millions logged	All patents	7.7	3.0	−5.5	12.2
			Willing patents	7.7	3.1	−5.5	12.2
4	Research intensity	R&D expenditure divided by revenue (where revenue measured in $US thousands)	All patents	3.2	66.4	0	7098
			Willing patents	3.9	80.3	0	7098
5	Prestige	Average number of non-self forward citations on patent stock within 5 years of each patent's granting date, where **patent stock** is comprised of the patents granted during the 5 years before patent granted	All patents	4.2	4.1	0	80.5
			Willing patents	3.8	3.7	0	68.7
6	Age	Years between patent owner's incorporation and patent application	All patents	22.8	19.9	0	102
			Willing patents	21.0	18.8	0	102
7	Experience	Number of outward licensing agreements by patent owner during 5 years before patent application	All patents	10.3	15.9	0	107
			Willing patents	9.2	14.7	0	107
8	Depth	Number of patents granted by patent owner in patent's IPC (international patent category) in 5 years before patent granted	All patents	90.2	127.6	0	2329
			Willing patents	68.9	102.4	0	2329
9	Breadth	Number of different IPCs in patent owner's patent stock	All patents	27.1	34.6	1	302
			Willing patents	27.7	37.3	1	302
10	Average licensing speed	Average licensing speed for all licensed patents by patent owner	All patents	5514.9	2572.8	0	7280
			Willing patents	5596.6	2533.4	0	7280
Patent variables							
11	Complexity	Number of technological claims made by patent	All patents	17.7	16.9	1	683
			Willing patents	17.3	16.2	1	390
12	Forward citations	Number of forward citations received by the patent	All patents	2.6	5.3	0	128
			Willing patents	2.8	5.5	0	107
13	Scope	Number of IPCs listed on patent	All patents	2.2	1.4	1	25
			Willing patents	2.2	1.4	1	25

Firms without licensing history are given longest avg speed +1 of firms with licensing history.

Table 1b
Statistics of variables, licensed patents (n = 117).

	Variable	Measure	Mean	Std. Dev.	Min	Max
Dependent variables						
1	Licensing speed	Number of days between patent application and license agreement for same patent	2214.3	1222.9	55	5793
2a	Lump-sum payment	Sum of all the lump-sum payments made to the licensor for the agreement, $US millions	58.2	106.8	0	515
2b	Royalty rate	Percentage of future royalties to be paid to the licensor based on commercialized product	12.8	16.8	0	55
Licensor variables						
3	Size	Licensor revenue in millions of $US, logged	2.5	2.8	−5.3	10.9
4	Research intensity	R&D expenditure divided by revenue (where revenue measured in $US thousands)	18.8	121.6	0.01	1322
5	Prestige	Average number of non-self forward citations on patent stock within 5 years of each patent's granting date, where **patent stock** is comprised of the patents granted during the 5 years before patent granted	6.4	10.9	0	68.7
6	Age	Years between patent owner's incorporation and patent application	10.5	8.6	0	38
7	Experience	Number of outward licensing agreements by patent owner during 5 years before patent application	6.7	10.4	0	59
8	Depth	Number of patents granted by patent owner in patent's IPC (international patent category) in 5 years before patent granted	34.0	214.6	0	2329
9	Breadth	Number of different IPCs in patent owner's patent stock	4.2	5.4	0	36
10	Average licensing speed	Average licensing speed for all licensed patents by patent owner	3304.1	2933.8	10	7280
Patent variables						
11	Complexity	Number of technological claims made by patent	25.9	30.7	1	265
12	Forward citations	Number of forward citations received by the patent	0.7	1.2	0	6
13	Scope	Number of IPCs listed on patent	2.2	1.4	1	6

Table 2a
Variance inflation factors and correlation of variables, willing patents (n = 34,660).

	Variable	VIFs	2	3	4	5	6	7	8	9	10	11	12	13
Dependent variable														
2	Licensing speed		1											
Licensor variables														
3	Size	1.5	0.02	1										
4	Research intensity	1.0	−0.02	−0.15	1									
5	Prestige	1.1	0.01	−0.11	−0.01	1								
6	Age	1.5	0.08	0.43	−0.03	0.05	1							
7	Experience	1.2	−0.31	0.14	−0.02	−0.03	0.01	1						
8	Depth	1.3	−0.06	0.32	−0.02	0.02	0.42	0.20	1					
9	Breadth	1.3	0.28	0.42	−0.03	0.03	0.45	−0.15	0.18	1				
10	Average licensing speed	1.6	−0.01	0.19	−0.003	0.03	0.09	−0.25	0.05	0.21	1			
Patent variables														
11	Complexity	1.0	−0.10	−0.12	0.02	0.05	−0.06	−0.02	−0.03	−0.08	−0.03	1		
12	Forward citations	1.1	−0.07	−0.10	0.01	0.21	−0.01	−0.04	0.01	−0.02	0.08	0.16	1	
13	Scope	1.1	−0.07	−0.08	0.02	−0.09	−0.08	0.08	−0.02	−0.14	−0.11	0.04	−0.10	1

4.1. Payoffs to Licensor

The results suggest that patent owners with characteristics of prominence and knowledge structuration achieve licensing deals slowly. This begs the question whether this speed is beneficial. That is, does reaching a licensing deal slowly result in a higher payoff for the licensor? The results for the final stage of the system described in Eq. (2) are presented in Table 4, where the first column uses *Lumpsum payment* as the dependent variable and the second column uses *Royalty rate*. As there may be a substitution effect between the royalty rate and the lump-sum paid to the licensor, we follow Sakakibara (2010) in using the three-stage least square (3SLS) regression to estimate the two equations simultaneously. The 3SLS approach accounts for possible interdependence between the two dependent variables.[11] The regression in Table 4 is performed on the patents that were actually licensed (n = 117) and, as such, we will now refer to the patent owners as licensors.

The results show that slower licensing speeds are associated with higher royalty rates (Hypothesis 4). There is strong evidence that licensor size, research intensity, and prestige and patents with a high number of forward citations and scope, reduce royalty rates. Licensee size and patent complexity act to increase lump-sums.

[11] We also include the independent variable licensee size in both payoff regressions to control for the situation when royalty rates do not correlate to licensor royalty payments because the final drug sales are very high while the royalty rates are low (Sakakibara, 2010).

Table 2b
Variance inflation factors and correlation of variables, licensed patents (n = 117).

	Variable	VIFs	1	2a	2b	3	4	5	6	7	8	9	10	11	12	13
Dependent variables																
1	Licensing speed		1													
2a	Lump-sum payment		0.22	1												
2b	Royalty rate		0.07	0.19	1											
Licensor variables																
3	Size	1.6	0.15	−0.06	−0.18	1										
4	Research intensity	1.0	0.13	−0.02	0.09	−0.32	1									
5	Prestige	1.1	0.22	0.20	0.04	0.09	−0.04	1								
6	Age	1.3	0.06	−0.08	−0.03	0.39	0.02	−0.09	1							
7	Experience	1.4	0.11	−0.02	−0.10	0.31	−0.03	0.18	0.09	1						
8	Depth	1.2	−0.03	0.01	0.00	0.08	−0.02	−0.05	0.23	0.04	1					
9	Breadth	1.6	0.02	−0.14	−0.15	0.60	−0.05	0.05	0.34	0.53	0.02	1				
10	Average licensing speed	1.3	−0.11	−0.08	−0.24	0.08	−0.02	−0.10	−0.08	0.01	0.13	0.10	1			
Patent variables																
11	Complexity	1.1	−0.03	0.21	0.09	−0.09	0.07	−0.04	0.16	0.02	0.02	−0.01	−0.23	1		
12	Forward citations	1.2	−0.05	−0.01	0.01	0.05	0.02	0.40	−0.06	0.05	0.17	0.10	−0.05	0.07	1	
13	Scope	1.1	0.19	0.04	−0.02	0.08	0.04	0.02	−0.05	0.05	−0.07	0.05	−0.06	−0.09	−0.19	1

Table 3
Lognormal duration model with selectivity.[a]

Dependent variable	Regression 1		Regression 2		Regression 3	
	Willing Column 1a	Licensing speed Column 1b	Willing Column 2a	Licensing speed Column 2b	Licensing speed Column 3a	Licensing speed Column 3b
Licensor variables						
Size	0.03 (0.012)***	0.45 (0.097)***			0.03 (0.012)***	0.31 (0.075)***
Research intensity	0.001 (0.0003)*	0.01 (0.004)*			0.001 (0.0003)*	0.01 (0.004)
Prestige	−0.04 (0.007)***	−0.14 (0.033)***			−0.04 (0.007)***	0.004 (0.015)
Age	−0.01 (0.002)**	−0.04 (0.019)*			−0.01 (0.002)**	−0.01 (0.014)
Experience	−0.004 (0.002)**	0.001 (0.021)			−0.004 (0.002)**	0.01 (0.018)
Depth	−0.002 (0.0002)***	−0.01 (0.002)***			−0.002 (0.0002)***	0.002 (0.001)**
Breadth	0.001 (0.001)	0.15 (0.068)**			0.001 (0.001)	0.12 (0.059)**
Average licensing speed	0.00001 (0.00002)	0.0003 (0.0001)***			0.00001 (0.00002)	0.0002 (0.0001)***
Patent variables						
Complexity			−0.002 (0.001)	−0.02 (0.004)***	−0.001 (0.001)	−0.01 (0.004)***
Forward citations			0.004 (0.003)*	0.33 (0.081)***	0.01 (0.003)***	0.33 (0.076)***
Scope			0.003 (0.012)*	0.13 (0.094)	−0.004 (0.010)	0.27 (0.109)**
Constant	0.49 (0.141)***	12.47 (0.901)***	0.67 (0.048)***	16.50 (0.989)***	0.51 (0.136)***	12.47 (0.753)***
Wald Chi−squared	150.72*** (8 d.f.)		4.46 (3 d.f.)		190.13*** (11 d.f.)	
Log Pseudo L'd	−34,248.9		−36,704.3		−34,187.6	

[a] Two stage model with patent willingness to be licensed in first stage (selectivity) and time to licensing in the second stage (duration).
Standard errors clustered on repeated licensors. Dursel command in STATA.
Note:Number of observations: 54,593 first stage and 34,660 second stage.
* Indicates significance at ≪10%.
** Indicates significance at ≪5%.
*** Indicates significance at ≪1%.

5. Discussion

In this study, we investigated two questions: Which licensor and patent characteristics determine the speed of licensing? How does the speed of licensing impact the royalties and lump-sum payments to licensors? We addressed these questions by proposing that licensing speed is influenced by variables for licensor prominence, licensor knowledge structuration, and patent desirability. These variables work to increase the size, complexity and duration of the licensing-out task, while also allowing licensors to take their time to review, negotiate and select a higher royalty rate. Our findings have a number of implications for research on innovation dynamics, technology licensing and related management practice, which we now discuss.

The fundamental contribution of our study is that it advances current understanding of one aspect of innovation speed. As competitive advantages are temporary, the speed of innovation, and, in particular, the allure of being fast at innovation, has appealed to managers, scholars and journalists. However, while this prevailing discourse is attractive, scholars have seldom empirically investigated the determinants of innovation speed, and even less research attention has been given to studying the benefits of being fast

Table 4
Licensor payoffs, simultaneous equation regression.[a]

Dependent variable	Lumpsum payment	Royalty rate
Licensing speed[b]	−0.01 (0.027)	0.02 (0.005)***
Licensor variables		
Size	8.19 (6.135)	−2.88 (1.012)***
Research intensity	0.09 (0.116)	−0.04 (0.019)**
Prestige	2.06 (1.481)	−0.53 (0.244)**
Age	−1.75 (1.192)	−0.04 (0.196)
Experience	0.25 (1.145)	0.08 (0.189)
Depth	0.02 (0.043)	0.01 (0.007)
Breadth	−4.37 (2.663)*	0.60 (0.439)
Patent variables		
Complexity	0.88 (0.289)***	0.05 (0.047)
Forward citations	11.45 (8.256)	−0.59 (1.362)***
Scope	11.05 (8.381)	−3.32 (1.383)**
Control		
Licensee size	14.94 (3.369)***	0.91 (0.556)
Constant	16.95 (52.086)	−10.26 (8.597)
Chi-square	40.46***	24.54**
Adjusted *R*-squared	0.25	0.17

[a] Presented results are the last stage of a two stage system, where the first stage is the duration model for the 117 licensed patents and the second stage is the licensor payoffs.
[b] *Licensing speed* is estimated using a 3-step procedure outlined in Angrist and Pischke.
Notes: Number of observations: 117.
* Indicates significance at ≪10%.
** Indicates significance at ≪5%.
*** Indicates significance at ≪1%.
The error terms in each regression are linked using a 3SLS regression (see Sakakibara (2010) for similar approach).

or slow at innovation. Consequently, there have been calls for more specific and nuanced studies of the determinants and benefits of innovation speed (Carbonell and Rodriguez, 2006; Chen et al., 2005). Our study addresses these calls by focusing on one important aspect of innovation speed (i.e., the speed of licensing) and by directly measuring it (i.e., the time elapsed from filing a patent for a technology to announcing it has been licensed) and its payoffs to licensors.

One major implication of our study, it that while our results reinforce the notion that innovation speed is important, when it comes to licensing, it is beneficial for licensors to slowly and carefully license-out patented technologies. This adds to related research on optimal licensing arrangements, which has found that the level of lump-sum payments and royalty rates are determined by the extent of knowledge transfer needed in the relationship (Macho-Stadler et al., 1996; Hegde, 2014). Royalty rates tend to be higher for licensing contracts with knowledge transfer (Macho-Stadler et al., 1996) while lump-sum payments tend to be higher in contracts that the licensor suspects the licensee intends to shelve the technology (Hegde, 2014). Our study expands the optimal contract literature by showing that slower licensing results in greater royalty rates for the licensor. This suggests that in the same way that management approaches can and should vary across the whole innovation process (i.e., the "fuzzy" front end versus the linear and controlled final stages of the process) (McCarthy et al., 2006), there will also be different optimal paces for the stages of the innovation process. The determinants and outcome of innovation speed is a complex concept, and one speed is unlikely to fit or benefit all stages of the innovation process. And in the case of licensing biotechnology patents, we find that licensing slowly rewards a "less haste, greater payoff" approach to this stage of innovation.

A second major implication of our results is that we are the first to examine the role that licensor prominence plays in the licensing speed. This is important as it shows that licensing is not just a functional transaction based solely on the quality and suitability of a patent. Organizational perceptions about some aspects of prominence matter. Thus, similar to Podolny (1993) and Sine et al. (2003), our results demonstrate that with the uncertainty that comes with licensing-in technologies, licensor prominence is a signal of quality to licensees. Also, Higgins et al. (2011) show that the scientific status of firms, and more specifically the employment of star scientists, provides a signal of firm quality to potential investors and allows licensors to distinguish themselves over and above the quality of their patent. Like each of these studies, we show how firm prominence signals greater visibility and that helps attract the attention of possible partner firms. This in turn increases the size, complexity and duration of the licensing- out task, while also allowing licensors to negotiate and select an agreement with a higher royalty rate.

A third major implication of our study is that it is the first to show that a licensor's knowledge base and related organizational learning capabilities (knowledge structuration) influence the speed of licensing. A licensor with deep knowledge in a technological area will be well known to potential licensees who operate in the same technological areas. This familiarity not only results in licensing – out opportunities that allow licensors to carefully review agreement options; it also induces licensors to be cautious. When a firm's technological knowledge is deep, licensors are wary of the risks of knowledge being inadvertently revealed to partners (Zhang and Baden-Fuller, 2010). In terms of knowledge breadth, when a licensor possesses broad knowledge, it will likely be more open to and known by a greater number of licensees across this wide-ranging knowledge base. Also, licensors with broad knowledge will be attractive to licensees as they more likely produce innovations based on valuable architectural knowledge (Henderson and Clark, 1990), and have the better abilities to transfer the technology (Ceccagnoli and Jiang, 2013). Our results support these arguments that deep and broad knowledge confer licensors with opportunities and stances that work to slow down the speed of licensing.

5.1. Limitations and future research

Of course, there are limitations of this study that are worth noting, as they also offer opportunities for future research. First, by focusing on one stage and aspect of innovation (the speed of technology licensing), we are considering only the latter stage of the innovation process. While this limitation is by design so as to provide the framing for a rigorous study of one part of innovation speed, this means there are two other stages to be studied: the conception of an idea, and the development that idea (Kessler and Chakrabarti, 1996). These stages will also have speeds, and the findings and implications from our study may not apply to these stages. Thus, future research could focus on these two earlier stages of the innovation process and explore the pace at which firms generate and develop their innovation ideas.

Second, our paper has limitations related to our use of data from the biotechnology industry and the nature of its technology. While restricting our sample to one industry helps to make our models more accurate and robust, it is at the expense of limiting the extent to which our findings might directly be applied to other industries. This is especially the case for technology industries that tend not to patent (e.g., software) and non-technology industries that rely on copyrights and trademarks to protect and license their intellectual property (e.g., entertainment). Also, license exclusivity has been found to support a technology's commercialization potential (Somaya et al., 2011), but licensing is almost entirely exclusive in the biopharmaceutical industry, making it impossible to test its impact on the speed of licensing.

Third, as it is not possible to fully control for all the drivers of licensing in one study, we highlight some other factors future studies might control for. For example, we do not consider the possibility that the licensee may be willing to accept a license at unfavorable terms. This could happen to prevent associated risks and costly litigations that the licensee may be facing. Also, we were not able to control for cross-licensing in our data. While we believe this type of licensing activity is limited in biopharmaceutical industry (see Gambardella et al., 2007), future research could consider the dynamics of licensing in industries where the incidence of cross-licensing is much higher (e.g., software and electronics). And although it is more of an issue for software patents, inventing around a biopharmaceutical patent does occur (Cohen et al., 2000) and it may be possible that this could affect licensing speed. Furthermore, it seems likely that the speed of licensing will also depend on the nature of the clauses included in a contract. We were not able to review the contract clauses to see how they might restrict or encourage faster negotiations.

Finally, technology licensing is just one mechanism by which firms commercialize their innovations. Other approaches include the sale of technology (Caviggioli and Ughetto, 2013), inter-firm alliances (Eisenhardt and Schoonhoven, 1996; Gulati et al., 2009), the creation of new ventures, and the role of patent intermediaries: organizations that facilitate the exchange of IP (Hagiu and Yoffie, 2013). Each of these approaches provides an opportunity for future research on the determinants and payoffs of being fast or slow at this stage of the innovation process.

6. Conclusion

While it is clear that speed is a popular and important characteristic of innovation, there is mixed empirical support for the benefits of innovating quickly or slowly. In response, we focus on one stage of the innovation process: commercialization and, in particular, the determinants and benefits of licensing speed. Possibly our most important finding is that unpacking the speed of innovation provides interesting and counterintuitive insights. We predict and find that strength in licensor prominence, licensor knowledge structuration, and patent appeal reward a “less haste, greater payoff” approach to this stage of innovation. We suggest this boils down to the allure and status effects of these licensor variables. They help licensors discover and be discovered by licensees, resulting in a wealth of agreement options and a strong licensing-out position for licensors. This not only increases the size, complexity and duration of the licensing out-task, but allows licensors to take their time to review, negotiate and select the most attractive royalty rate.

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