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Why Do Some Patents Get Licensed While Others Do Not?

Karen Ruckman[1,*] and Ian McCarthy[2]

[1] Beedie School of Business, Simon Fraser University, Burnaby, British Columbia, Canada. email: ruckman@sfu.ca and [2]Beedie School of Business, Simon Fraser University, Burnaby, British Columbia, Canada. email: imccarthy@sfu.ca

*Main author for correspondence.

Abstract

To understand why some patents get licensed and others do not, we estimate a portfolio of firm- and patent-level determinants for why a particular licensor's patent was licensed over all technologically similar patents held by other licensors. Using data for licensed biopharmaceutical patents, we build a set of alternate patents that could have been licensed-in using topic modeling techniques. This pro-vides a more sophisticated way of controlling for patent characteristics and analyzing the attractive-ness of a licensor and the characteristics of the patent itself. We find that patents owned by licensors with technological prestige, experience at licensing, and combined technological depth and breadth have a greater chance at being chosen by licensees. This suggests that a licensor's standing and or-ganizational learning rather than the quality of its patent alone influence the success of outward licensing.

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1. Introduction

The global licensing market was estimated to be worth $200 billion in 2011 (Alvarez and L opez, 2015) and licensing royalty payments grew at a rate of almost 10% between 1990 and 2003 (Athreye and Cantwell, 2007). At the same time, however, numerous patents remain unlicensed (Gambardella et al., 2007) and many firms have difficulty find-ing licensing partners (Zuniga and Guellec, 2008; Kani and Motohashi, 2012). Reconciliation of this puzzle is central to the call to better understand why firms choose each other for a licensing agreement (Kim and Vonortas, 2006a; Arora and Gambardella, 2010a).

To address this research opportunity, we examine the impact of eight licensor characteristics and four patent characteristics on the ability of a patent owner to be identified and selected by a buyer. In varying and overlapping ways, the firm-level determinants reflect the search and learning capabilities of the licensor, as well as its visibility and attractiveness. The patent-level determinants control for differences in patent quality. Three of the firm-level de-terminants (licensor prestige, licensor technological depth, and licensor technology breadth) are new to the licensing research literature and allow us to examine how the licensor characteristics act as signals that help licensees to iden-tify, evaluate, and choose a licensor and its patent over licensors with similar patents. While the other determinants have been examined in previous studies, we confirm or refute previous findings using a more sophisticated empirical method of identifying alternate patents.

Examining which licensor characteristics appeal to licensees is important because it answers calls to incorporate the demand side of licensing into the analysis of licensing activities (Arora and Gambardella, 2010b; Ceccagnoli and Jiang, 2013). The prior literature on licensing is largely from a supply perspective, i.e., what determines the propen-sity to engage in licensing-out. This research has mixed results; finding that small licensors (Gambardella et al., 2007) and both small and large licensors (Zuniga and Guellec, 2008) are more likely to out-license technologies. The rate of outward licensing is also positively associated with very small and very large licensors (Motohashi, 2008), cur-rent patent stock and past history in licensing (Kim and Vonortas, 2006b), and negatively related to large market shares (Fosfuri, 2006) and the disclosure of too much or too little voluntary information (Wuyts and Dutta, 2008). Our analysis sheds light on the licensor- and patent-level characteristics that are associated with increasing licensing probability by fixing the licensee perspective on only those patents that are technologically similar.[1]

Our study makes an empirical contribution by building on previous licensing likelihood studies and addressing the problem of which licensor–licensee pairs to include in the analysis. In previous licensing probability studies (e.g., Kim and Vonortas, 2006a; Kim, 2009), all known licensors were paired with all known licensees. Indeed, this is also the case for alliance probability studies such as Diestre and Rajagopalan (2012) and Rothaermel and Boeker (2008) where all known alliance partners are paired. This method conflates the possible technological motivations for poten-tial licensing agreements, leading to the overemphasis of licensing determinants as they were compared to licensing pairs that would have no feasible reason to license with each other. In our study, we use a text analytics approach called topic modeling (Kaplan, 2012; Venugopalan and Rai, 2014) to identify alternative patents that could have been licensed-in but were not by examining the text in each patent's abstract. This technique enables us to identify re-markably similar patents for each licensed patent allowing the analysis to disregard the technological motivation for the licensing agreement and instead focus on the attractiveness of the patent owner and the patent itself. In doing so, we are able to incorporate the demand side of the licensing transaction which previously had been under-represented in licensing literature (Arora and Gambardella, 2010b).

We examine the determinants of licensing using 93 licensing agreements in the worldwide biopharmaceutical sec-tor in a panel data set spanning 1993–2007. We find that licensors with strength in technological prestige, licensing experience, and combined technological depth and breadth are more likely to license-out their patents. The results also indicate that newer and highly cited patents are more likely to be licensed. Together these results offer a deeper understanding of licensing patterns and reveal the licensor characteristics that licensees prefer. This is inherently use-ful on a managerial level for firms looking to license-out as well as in-license. For instance, a licensor cannot control the attributes of a potential licensee but it can understand which of its own attributes will appeal to licensees. These attributes could be developed and promoted to help make a licensor more visible, viable, and ultimately attractive to potential licensees.

2. Determinants of licensing-out probability

Technology licensing involves the transfer of intellectual property (IP) between two parties: the owner of the IP (the licensor) and the buyer (the licensee). The licensor seeks to extract value from it in the form of licensing revenues and may be motivated to license-out their technologies because they lack the financial, physical, or intellectual resources to commercialize it. The propensity to license-out is associated with very small and very large licensors (Gambardella et al., 2007; Motohashi, 2008; Zuniga and Guellec, 2008), but also current patent stock and past history in licensing (Kim and Vonortas, 2006b). Licensees, on the other hand, typically acquire patented technologies as a means of di-versifying their technological assets or satisfying a particular internal technological gap. The motivation to do so may be inversely related to the licensee's level of internal research. Ceccagnoli et al. (2010) found that firms with higher R&D productivity and more complementary resources will be less likely to externally source their technology.

Licensing is a process where both parties want to pair with the best possible partner. Once one looks beyond the technological motivation for a particular licensing agreement, the choice of a particular licensor's patent to license-in over other technically similar patents can be a complicated decision involving the ease of identification of the patent and the licensor, the attractiveness of the licensor's technical prowess bargaining strength, and projections about the

1 It is important to note that this analysis is not a matching study or an experiment of the actual patents that the licensees chose between. The comparison of the alternate patents to the actual licensed patent allow us to ascertain the charac-teristics that are correlated with the licensee choice.

licensor's future knowledge transfer capabilities. We now introduce determinants for this licensing probability and discuss how each one affects the ability of a licensor to get its patent licensed. We focus on three determinants (licen-sor prestige, licensor technological depth, and licensor technology breadth) that have not been previously examined in the licensing probability or propensity literatures. We argue that these are important for understanding how licen-sor visibility, credibility, and learning impact the probability a licensor's patent will be licensed over technologically similar patents held by other licensors.

2.1 Licensor prestige

Licensor prestige is the extent to which a licensor is viewed favorably by all licensees. Drawing on prior research that shows that institutional prestige increases a licensor's rate of licensing (Sine et al., 2003), there are four reasons why licensor prestige makes a licensor more attractive as a licensing partner.

First, patents owned by licensors that are thought to have high prestige will be more attractive to licensees due to a "halo effect" (Thorndike, 1920, p. 25). This effect is a confirmation bias about a firm's reputation, which allows firms to better attract resources and opportunities (Roberts and Dowling, 2002). For licensors, their reputation is based on the quality of its key productive resources including, for example, star scientists in biotechnology firms (Audretsch and Stephan, 1996) and the quality of patent stocks (Alcacer & Gittelman, 2006; Marco, 2007). When li-censees perceive licensors to be strong at one or more of these research indicators they transfer this positive percep-tion to the strategic and commercial attractiveness of the licensors and their technology. For example, research shows that the halo effect enables universities with strong research standings to license-out more than their lower standing research counterparts (Sine et al., 2003).

Second, prestige increases a licensor's visibility, which is the extent to which potential licensees will know about a licensor's patents. This phenomenon is explained using Merton's (1968) seminal work on the Matthew effect (i.e., the rich get richer), which found that scientist prestige heightens the visibility of these scientists over less prestigious scientists with the same quality of scientific research. Similarly, research on mergers and acquisitions shows that the higher the average quality of a firm's patent stock (as measured by forward citations), the greater the interest in acquiring the firm (Grimpe & Hussinger, 2008). In the licensing context, we suggest that strong prestige enhances the visibility of a licensor, thereby increasing the likelihood that potential licenses will be aware of the licensor (Lewin, 1935; Granovetter, 1985; Sine et al., 2003).

Third, licensor prestige increases the legitimacy of the claims in a licensor's patent. That is, the more respected is a licensor, the more likely licensees will view the licensor's patent and technological claims as being credible. The cred-ibility afforded by a licensor's strong prestige will make a patent more attractive for licensing purposes. Conversely, licensees will more likely doubt technological claims from less prestigious licensors and be less enticed to complete a licensing agreement. This credibility effect of prestige has been shown in the placement of researchers into job pos-itions (Flanagin and Metzger, 2007). The more prestigious a researcher's training institute, the higher the quality of the institute the researcher is placed in.

Fourth, licensees prefer to transact with more prestigious licensors as it increases their own prestige (Sine et al., 2003). Individuals, teams, and firms can all build their own prestige by association, and in turn increase their stand-ing, visibility, and credibility. For example, to compensate for liabilities of newness, start-up ventures often seek to borrow reputation by association by forming a partnership with prestigious venture capital firms (Larson and Starr, 1993). This effect applied to licensing would mean prestigious licensors are more likely to attract potential licensees interested in licensing their technologies and the benefits of association in doing so.

In summary, prestigious licensors will have a greater chance of licensing-out because licensees are more likely to know about and be attracted to them due to the increases in licensor standing, visibility, credibility, and the benefits by association (Sine et al., 2003).

2.2 Licensor technological depth

Licensor technological depth is the extent to which a firm has specialized in an area of technological knowledge and is associated with post-contractual knowledge transfer and the ability of the licensor to convey knowledge effectively to the licensee. Drawing upon the organizational learning literature, a firm's depth of technological knowledge in the licensed patent's technological area is positively linked to knowledge transfer (Wu and Shanley, 2009) and particu-larly in the biopharmaceutical industry, where expertise in disciplinary areas is crucial (Henderson and Cockburn, 1994).

Technological depth acts as a signal to others of their technical expertise in a particular technical area (Arora and Gambardella, 1990). Firms with strong technological depth are attractive to other firms in need of supplement-ing their own knowledge through partnerships (Stuart, 1998; Baum et al., 2000) and will result in more firms willing to partner with them (Ahuja, 2000).

Technological depth, like prestige, acts like a beacon, helping licensors to be identified. While searching patent databases, licensees will encounter various patents in technological areas similar to those that are sought. Licensors with technological depth in the sought area will be more likely to be encountered. Thus, greater technological depth or expertise helps make licensors more noticed, noted, and selected by licensees. It is also likely that licensees per-forming local searches (i.e., search for knowledge that is closely related to a firm's preexisting knowledge base) may already be familiar with the prospective licensor (Katila and Ahuja, 2002, Laursen, 2012). The patents, therefore, owned by licensors with strong technological depth will likely be more known to prospective licensees than patents owned by licensors with less technological depth.

2.3 Licensor technological breadth

Technological breadth refers to the variety or scope of technological knowledge areas a firm has explored (Wang and von Tunzelmann, 2000; Katila and Ahuja, 2002; Lodh and Battaggion, 2015). As breadth of technological knowledge has been found to be an important component of organizational learning (Zahra and George, 2002), we assert that it is also a quality that makes licensors attractive to licensees. A licensor with a broad technological knowledge base is better able to disseminate its technology to external parties. Cohen and Levinthal (1990: 136) acknowledge that some fraction of a firm's knowledge "must be fairly diverse to permit effective, creative utiliza-tion of the new knowledge" by another firm. Similarly, Lane and Lubatkin's (1998) research found that alliance partners' knowledge bases must be different in some way for firms to fully take advantage of learning opportuni-ties. We argue that licensor technological breadth helps facilitate knowledge transfer to the licensee through the ef-ficient transmission of knowledge, making the licensor more attractive for licensing agreements. This is consistent with both Contractor (1981) and Teece (1977) who emphasized that suppliers' knowledge transfer capability is an important factor in lowering buyers' integration costs and Ceccagnoli and Jiang (2013) who found that licensors with strong technological breadth can more expertly communicate relevant knowledge to the licensee. This endows licensors with a knowledge transfer ability that makes the patents owned by those licensors more likely to be in-licensed by licensees.

2.4 Other established licensor determinants

Previous research on licensing propensity has focused on five other established firm-level determinants. As high-lighted earlier, this literature has not examined these determinants by controlling with a set of technological equiva-lent patents that could have been licensed. As this is the approach we take in this article, we can corroborate extant results for these five determinants. We now introduce each one briefly here.

Licensor size is a simple indicator of a firm's complementary assets. As we focus on biotechnology patents, firms with more downstream assets (e.g., drug manufacturing facilities) are expected to be less inclined to license-out. This determinant has been well established in its negative influence on firm licensing activities (Gambardella et al., 2007; Kani and Motohashi, 2012) and participation in alliance agreements (Ahuja, 2000; Colombo et al., 2006). However, in contrast, Kim (2009) and Kim and Vonortas (2006a) argue that large licensors are more likely to license-out to better exploit their technologies.

A licensor's experience at licensing is the second recognized determinant that we consider. Generally, firms ac-quire knowledge, learn, develop capabilities, and get better at doing things with experience (Dodgson, 1993). In the context of licensing, experience allows licensors to learn from past licensing decisions and apply that knowledge to future choices. Licensor's past history of licensing transactions (experience) has been shown to positively affect licens-ing likelihood (Kim and Vonortas, 2006a,b; Kim, 2009).

The third established determinant, research intensity, is a proxy for the concentration of a biopharmaceutical firm's total R&D inputs to the innovation process (Cohen and Levinthal, 1990). In any technology-based firm, the amount of internal R&D is expected to promote collaboration (Katila and Mang, 2003) and influence a firm's motiv-ation to license-out (Lane and Lubatkin, 1998; Zhang and Baden-Fuller, 2010). Licensor research intensity is ex-pected to be a positive influence on licensing likelihood (Kani and Motohashi, 2012).

Research age is the fourth established determinant we consider. It is the length of time a licensor has been actively researching and is a proxy for the licensor's legitimacy, power, and standing. For biopharmaceutical firms it has been found that there is a greater chance of alliance participation when partners are technologically similar (Rothaermel and Boeker, 2008).

The fifth established determinant is the past relationships between a licensor and licensee. The greater the past relationships, the more familiar a licensor and licensee should be with each other. This is expected to greatly reduce the transaction costs associated with licensing and has been found to increase licensing likelihood (Kim and Vonortas, 2006a; Kim, 2009).

3. Empirical section

3.1 Model

Following Ruckman (2005) and Colombo et al. (2006), the model of the licensee's choice decision is:

$$y^*_{ijpt} = V[\beta' x_{ijpt} + \varepsilon_{ijpt}] \text{ where}$$
$$\beta' x_{ijpt} = \beta'_1 x_{it} + \beta'_2 x_{jt} + \beta'_3 x_{pt} \tag{1}$$

y^*_{ijpt} is the unobserved variable that captures licensee i's decision to enter into a licensing agreement at time t of patent P owned by potential licensor j. The vector of explanatory variables (x_{ijpt}) includes licensee-, licensor-, and patent-specific characteristics. The choice to license patent P occurs when the valuation of the agreement exceeds all others in the same choice set P. The valuation is determined at the time of the licensing agreement and thus is calculated as the present value of all future revenue streams arising from the agreement less costs (Kim and Vonortas, 2006b). The observed outcome (y_{ijpt}) is defined as follows:

$$y_{ijpt} = 1 \ \ if \ \ V\left[\beta' x_{ijpt} + \varepsilon_{ijpt}\right] > V\left[\beta' x_{ijp't} + \varepsilon_{ijp't}\right] \forall p' \in P, 0 \ \text{ otherwise.} \tag{2}$$

All agreements in this model are exclusive contracts between one licensee and one licensor reflecting accepted prac-tice in the biopharmaceutical sector. The model structure has each known licensee choosing a patent to be licensed among all technologically similar and available patents at the time t of the agreement. As such, the pairings are licen-see–patent pairs, not licensee–licensor pairs.

The model fixes the licensee decision across all alternative patents. The approach, methodology, and the inter-pretation of the results differ from existing licensing probability studies (Kim and Vonortas, 2006a; Kim, 2009) which pair together all known licensors and licensees to form a matrix of potential dyads. The firm-level attri-butes of the successful dyads in those studies are interpreted as contributing to the likelihood of an agreement compared to all other potential agreements, many of which would involve technologies owned by licensors that the licensees would have no interest in acquiring. This results in the over-emphasis and mis-interpretation of firm-and patent-level characteristics contributing to the likelihood of an agreement. For instance, suppose the group of patents that were being chosen between all had similar licensor characteristics (e.g., prestige). In that case, the pre-vious technique would have inaccurately found those characteristics to be significant because it would have com-pared the chosen patents to all other patents which would have a variance of those characteristics. Our analysis, on the other hand, would find those determinants to be insignificant because they were not defining features of the chosen patent compared to its alternatives. In our model, the patents in each choice set are technologically close substitutes, making the potential licensee–patent pairings in our model realistic for the technological needs of each licensee. Effectively, this allows a careful examination of the demand for licensing because any licensee motivations to do with economies of scope or strategic fit of a particular technology are already accounted for. As such, the patent owner and patent attributes for each patent are observed by the licensee in each choice group and those attributes are interpreted to be attractive to the licensee or unattractive solely on the basis of those attributes.

As the dependent variable is binary, the estimation will be in the logistic functional form, however, as there are separate choice groups for each known agreement, there are two choices for the estimation method: fixed effects method (called conditional logit) or random effects method. Conditional logit uses fixed effects to account for each choice group[2] and, in doing so, all the variables that do not vary within a group drop out of the regression (Ruckman, 2005; Palomeras, 2007). In our model, this would be all the licensee-specific characteristics. If random ef-fects for each choice group are used instead of fixed effects, all group-unvarying variables are retained but will intro-duce bias in estimates (Allison, 2009; Bell and Jones, 2015). The Hausman test is a common method of determining the best model and it does not reject the hypothesis that random effects are a consistent and efficient estimator of the true parameters (Chi-squared (12 d.f.) ¼ 15.6, P-value ¼ 0.21), indicating that neither model is preferred over the other. However, Clark et al., 2015 find that fixed effects is the preferred model over random effects for data sets with within group standard deviation around 0.2 (ours is 0.18 while the standard is 1.0). We, therefore, present our analysis using conditional logit as the default model; however, we will also show results using random effects for comparison and robustness.

3.2 Identification of alternative patents

To identify the patents that are similar to the licensed patent, we employ text analytics which has been used recently in the context of patent classification (Bergmann et al., 2008; Wu and Huang, 2010; Gerken and Moehrle, 2012). Firms externally source technology sometimes to fill a particular internal technological gap (Higgins and Rodriguez, 2006; Danzon, Epstein and Nicholson, 2007) and it would be logical that these firms would consider various patents that fit the same technological profile and satisfy the same technological need. Patents are assigned classification codes which aim to categorize the technology and group together similar patents. However, the patent classification codes are very broad and subjective due to variations in judgments of the patent examiners (Venugopalan and Rai, 2014) leading any data based on them to be inaccurate (Dahlin and Behrens, 2005). We follow methods in Kaplan (2012) and Venugopalan and Rai (2014) which use the text analytics sub-branch called "topic modelling" to narrow down a broad list of patents to those that are most similar based on the text and terms found in their abstracts.

The topic modeling technique is a powerful and innovative way of dealing with large textual databases, enabling re-searchers to effectively sift through large sets of text to identify meaningful similarities (Thomas et al., 2014). This ap-proach has two advantages. First, it allows us to identify a very specific set of alternative patents that could have been licensed but were not. This enables us to narrow down the potential licensors (i.e., the supply side firms) to be only those that own the patents in a choice set.[3] Second, the topic modelling technique and the resulting conditional logistic analysis are performed at the patent-level. This makes it possible to control for patent-level characteristics that contrib-ute to the likelihood of an agreement, especially those associated with quality (Leone and Reichstein, 2012).

Topic model algorithms observe the collection of patents and reverse engineer the process by identifying a set of topics and a distribution of the patents over the topics that could have generated these patents. We used the MALLET toolkit (McCallum, 2002) to identify 500 distinct topics across the entire pool of patents[4] and the Kullback–Leibler distance measure (Bigi, 2003; Pinto et al., 2007) to determine the similarity of the distribution of each patents' topics to each licensed patent. Each choice set is composed of the 19 most similar patents to the licensed patent plus the licensed patent itself.[5] The topic modeling technique is described in detail in Appendix A.

There is a time-based limit to the value of patents leading licensees to discount old patents and instead consider relatively recent patents for possible in-licensing (Gans et al., 2007). Therefore, the set of patents that are available to license is further limited to those that were granted during the 5 years before the actual licensing agreement. Furthermore, we limit the set to only those patents that are owned by firms that have out-licensed one of their patents at least once before the time of the licensing agreement,[6] indicating that the licensor is an active out-licensor and that the other patents possessed by the firm are likely candidates for out-licensing as well.

2 Conditional logit directly accounts for heterogeneity between choice sets and latent individual licensee characteristics that could affect the licensee's valuation of a particular patent (like economies of scope or product gap).

3 That is not to say that the patents that the topic modeling technique identifies were the actual patents that the licensees considered for an agreement. This analysis is not an experiment and was performed entirely ex poste.

4 We offer robustness checks using 200 topics in Table A1.

5 Three choice sets had less than 20 patents in total. The rest had substantially more than 20. There are robustness checks on choice group sizes of 10 and 30 in Table A1.

6 This technique is similar to the grouping of licensing firms performed in Kani and Motohashi (2012). Those that have licensed out are considered to be active licensors and it is assumed that all of their patents are likewise willing to be out-licensed. Table A1 shows a robustness check that disregards potential licensors' licensing history.

The appropriateness of a binary choice to model licensing agreements depends in large part on the constraint of the choice by the focal firm (Mindruta et al., 2016). There are two criteria for the applicability of a discrete choice model over a matching model. First, licensees cannot face competition for preferred partners. Of our 93 agreements, four of them have alternate patents that were licensed by other firms. In addition, all four of these patents were licensed in separate choice groups, suggesting that the little competition that existed was very dilute. Second, licensees must have all the contracting power in a potential partnership. Our approach to our research problem assumes that licensees predominantly have the contracting power and choose across licensors. Previous alliance research in the bio-pharmaceutical industry suggests this is highly plausible (Rothaermel and Boeker, 2008; Diestre and Rajagopalan, 2012). Licensors are often smaller biotechnology firms focused on developing technologies to be licensed, while the licensees tend to be larger pharmaceutical firms that in addition to developing their own technologies will acquire technologies that they then manufacture and commercialize. These differences in firm size and scope produce a con-tracting power disparity where large licensees more commonly choose among several potential smaller licensors, un-like the opposite (Gambardella and Panico, 2014). To ensure the power dynamic is in the hands of the licensees, we have excluded licensors whose size is larger than the licensee in their choice group in our default results.[7] In addition, we explore whether the results differ when the contracting power increases for licensees by presenting results for when the licensors' sizes are less than 75% and 50% the size of their licensees. Given that the vast majority of the li-censees do not face rivalry constraints in choosing their preferred patent and that the power dynamic has been ensured to be with the licensees, a discrete choice analysis will be an appropriate analytical tool.

3.3 Data

Our data are for licensing agreements in the biopharmaceutical industry and were gathered from the RECAP data-base by Deloitte. RECAP is acknowledged to be the most complete database of the world's biopharmaceutical part-nerships (Schilling, 2009) and it has been used as a source of data in recent studies (Kollmer and Dowling, 2004; Wuyts and Dutta, 2008). An initial search of non-university[8] licensing agreements involving patents between 1993 and 2008 yielded 297 patents. After data matching across three databases, the default sample was reduced to 93 agreements.[9] The RECAP database also provided information about the past relationship history of each partner. Accounting data (revenues and R&D expenditures) for the firms were gathered using Compustat and filings with the US Securities and Exchange Commission. The data used to create the patent-based variables came from the NBER US patent citation data file (Hall et al., 2001) and its 2006 update. For patents granted after 2001, we performed dir-ect searches on the US Patent and Trademark Office patent database to compile accurate forward citations (for 5 years after their granting year).

The statistics of variables are in Table 1 are separated into summaries for all the patents in the choice sets (n ¼ 1848) and the licensed patents themselves (n ¼ 93). Interestingly, on average, it appears that successful licensors have lower depth, lower breadth, and lower experience than the pool of licensors. The correlations of variables are found in two tables. Table 2a displays the correlation for all patents in all choice sets and Table 2b for just the licensed pa-tents. The correlations for the successful licensors do not appear to be remarkably different than the pool of licensors. We will now discuss each variable's measurement.

Dependent variable: Chosen is a binary variable measured as 1 if patent is chosen by licensee for a licensing agree-ment, 0 otherwise.

Licensor variables: Technological prestige reflects the licensor's reputation for high-quality technologies. It is measured as a licensor's average number of non-self forward citations on patent stock within 5 years of each patent's granting. In as much as forward citations are correlated with value and importance of the technology (Harhoff et al., 2003; Lanjouw and Schankerman, 2004; Ceccagnoli et al., 2010), average firm-level forward citations reflect the

7 A robustness check in Table A1 includes all licensors, regardless of their sizes relative to their licensees.

8 Agreements involving university licensors were not included in the data set as university technology transfer offices have differing structures with different motivations (Markman, Phan, Balkin and Gianiodis, 2005) which may not emulate the other profit-driven firms in the sample.

9 The resulting data set limits the licensors in terms of company size (very small firms with no financial history are dropped), patenting history (licensors must have patented at least once), and licensing history (licensors much have had out-licensing history to be included). The average values of all variables before and after data arrangement are not significantly different: all but two variables are statistically equal by Welch's t-test.

Table 1. Statistics of variables

	Variable	Measure		Mean	Std. Dev.	Min	Max
Dependent variable:							
1	Chosen	1 if patent is chosen by licensee for a licensing agreement, 0 otherwise		0.05	0.2	0	1
Licensor variables:							
2	Licensor technological prestige	Licensor's average number of non-self forward citations on patent stock within 5 years after patent granted	All patents	4.5	6.5	0	63.3
			Licensed patents	8.9	15.2	0	63.3
3	Licensor depth	Number of patents granted to licensor in same IPC as licensed patent during 5 years before agreement, logged	All patents	2.3	1.4	0	6.3
			Licensed patents	0.4	0.7	0	3.3
4	Licensor breadth	Number of different IPC classes in licensor patents that were granted within 5 years before agreement	All patents	8.1	10.3	0	115
			Licensed patents	2.2	2.5	0	10
5	Licensor size	Licensor revenues in millions of $US, logged	All patents	4.2	3.1	–6.2	10.6
			Licensed patents	2.1	3.3	–6.2	9.7
6	Licensor experience	Number of license agreements during 5 years before agreement involving the licensor	All patents	15.1	14.9	0	94
			Licensed patents	9.6	14.1	0	56
7	Licensor research intensity	Licensor R&D expenditure divided by licensor revenue	All patents	14.7	128.3	0	4146.8
			Licensed patents	21.5	58.7	0.01	389.2
8	Licensor research age	Year of agreement minus year that licensor first applied for a patent	All patents	10.6	6.8	0	31
			Licensed patents	11.9	10.5	0	31
9	Past relationships	Number of relationships between licensee and licensor during 5 years before agreement	All patents	0.4	3.4	0	57
			Licensed patents	0.2	0.9	0	7
Patent variables:							
10	Patent complexity	Number of technological claims made by the patent	All patents	18.9	18.5	1	201
			Licensed patents	24.3	21.3	1	104
11	Patent age	Year of agreement minus year patent was granted	All patents	2.6	1.4	1	5
			Licensed patents	1.2	0.6	1	4
12	Patent scope	Number of IPC categories listed on the patent	All patents	2.5	1.5	1	17
			Licensed patents	2.3	1.4	1	7
13	Patent citations	Number of backwards citations listed on the patent	All patents	11.4	20.9	0	211
			Licensed patents	27.7	41.1	0	211

research reputation and technological legitimacy of a licensor. It is a firm-level characteristic that is particular to the licensing sector but could be applied to other technology-based but non-patenting industries by measuring references in industry reviews or technology awards. Leone and Reichstein (2012) use a similar measurement as a control vari-able when determining the speed of licensee post-contractual invention but do not explore it deeply or hypothesized about it. Kani and Motohashi (2012) also use the same measurement as a reflection of the potential demand for a li-censor's technology, although they do not find that it is significantly related to licensing propensity.

Depth is the number of patents granted to a firm in same International Patent Categories (IPC) as the licensed pa-tent during the 5 years before the agreement, logged. This variable indicates extent of a firm's existing knowledge in a particular technological area before a potential licensing agreement takes place and is similar to variables used in Leone and Reichstein (2012) ("unfamiliarity") and Sakakibara (2010) ("proximity to licensed patent technology").

Table 2a. Correlation of variables, all patents ($n = 1848$)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Chosen	1												
2	Licensor technological prestige	−0.16	1											
3	Licensor depth	−0.32	−0.15	1										
4	Licensor breadth	−0.13	−0.07	0.24	1									
5	Licensor size	−0.16	−0.06	0.32	0.47	1								
6	Licensor experience	−0.08	−0.04	0.3	0.18	0.63	1							
7	Licensor research intensity	0.01	0.01	−0.06	−0.05	−0.25	−0.08	1						
8	Licensor research age	0.04	−0.14	0.19	0.11	0.37	0.29	−0.04	1					
9	Past relationships	−0.01	−0.02	−0.004	0.01	0.14	0.22	−0.01	0.02	1				
10	Patent complexity	0.07	0.14	0.04	−0.03	−0.10	−0.09	0.01	−0.07	−0.02	1			
11	Patent age	−0.23	−0.08	0.11	−0.01	0.12	0.09	−0.01	0.26	−0.01	−0.05	1		
12	Patent scope	−0.02	−0.04	0.01	−0.02	−0.02	0.06	0.02	−0.04	−0.02	0.06	−0.01	1	
13	Patent citations	0.18	0.28	−0.01	−0.06	−0.14	−0.13	0.01	−0.09	−0.02	0.17	−0.09	−0.04	1

Table 2b. Correlation of Variables, licensed patents ($n = 93$)

	Variable	2	3	4	5	6	7	8	9	10	11	12	13
2	Licensor technological prestige	1											
3	Licensor depth	0.28	1										
4	Licensor breadth	0.28	0.49	1									
5	Licensor size	0.34	0.37	0.28	1								
6	Licensor experience	0.3	0.16	0.19	0.68	1							
7	Licensor research intensity	−0.15	−0.16	−0.21	−0.54	−0.16	1						
8	Licensor research age	−0.15	−0.09	−0.01	−0.08	−0.13	−0.01	1					
9	Past relationships	0.12	−0.09	−0.07	0.03	−0.02	−0.07	0.17	1				
10	Patent complexity	0.12	−0.13	−0.12	0.09	0.08	−0.04	0.21	0.13	1			
11	Patent age	0.14	0.28	0.14	0.31	0.28	−0.1	0.16	0.06	−0.01	1		
12	Patent scope	0.03	0.14	−0.04	0.04	0.15	−0.01	0.03	−0.08	−0.01	0.12	1	
13	Patent citations	0.52	0.07	0.06	−0.03	−0.14	0.01	−0.18	−0.06	0.18	−0.05	−0.16	1

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 firm patented in during the 5 years before the agreement. This particular measurement of technological breadth follows Zhang and Baden-Fuller (2010) and Leone and Reichstein's (2012) "technological diversity" variable.[10]

Drawing on prior studies on the motivations and capability to license, Size is measured as firm revenues in mil-lions of $US (logged); Experience is the number of licensing agreements a licensor has been involved with during the 5 years before agreement. As it has been shown that firms use the same internal division of experts to facilitate both inward and outward licensing agreements, the experience variable combines historical experience in both types of agreements. Lowe and Taylor (1998) found that firms that are proficient at inward licensing are often proficient in outward and vice versa, due to shared resources. We also measure Research intensity as research and development (R&D) expenditure divided by revenues. As this variable is broad in its measurement, its impact in this analysis is limited. Research age is measured as the year of the licensing agreement minus the year that the licensor first applied for a patent (Leone and Reichstein, 2012); Past relationships is the number of relationships between the licensor and licensee during the 5 years before agreement

10 We also perform a robustness check where this variable is measured as (1 – Herfindahl index of the IPC's that a firm has patented in). The results (not shown) are very similar.

(Vanhaverbeke et al., 2002). The types of relationships are broadly defined and can include licensing, alliances, or co-development agreements.

Patent variables: Patent complexity is the number of technological claims made by the patent (Lanjouw, 1999; Palomeras, 2007; Sakakibara, 2010). Patent age is measured as the year of licensing agreement minus the year the pa-tent was granted (Sakakibara, 2010) and is an indicator of remaining patent life. Patent scope is the number of IPCs listed on the patent (Gambardella et al., 2007; Sakakibara, 2010). Patent citations is the number of backward cit-ations listed on the patent (Palomeras, 2007) which captures the innovativeness of the technology.

3.4 Results

Table 3 reports the conditional logit regression results for the licensee choice of a patent to in-license. Given the non-linear nature of the dependent variable (Ai and Norton, 2003), the interactions were interpreted as multiplicative ra-ther than additive (Buis, 2010). Thus, odds ratios are reported which is equivalent to the exponent of the coefficients of the respective variables.[11] For instance, the estimated odds ratio for licensor size in Column 1 of Table 3 is 0.78. This is interpreted as follows: as licensor size increases by 1 unit ($10 million), the likelihood of an agreement de-creases by 22%.

Columns 1–3 in Table 3 display the results for the licensor explanatory, licensor control, and patent variables, re-spectively. Column 4 shows the regression with all the variables included and Column 5 includes an interaction term of licensor depth and breadth. The results indicate that licensors with strong technological prestige are more likely to be identified and have their patents chosen for a licensing agreement. A licensor's research reputation and techno-logical legitimacy can act as a beacon to increase the chances that its patent will be chosen by a licensee. Consistent with Kim, 2009; Kani and Motohashi, 2012; Kim and Vonortas, 2006b, patents owned by licensors that have exten-sive licensing experience are more likely to be licensed. The identification and communication afforded by experi-enced licensing teams makes a licensor more attractive for a licensing partnership.

Unexpectedly, patents owned by licensors with strong knowledge depth in the patent's technological area or with strong knowledge breadth were less likely to be chosen for a licensing agreement. This suggests that licensors with strong knowledge depth or breadth are unattractive to potential licensees when compared to other licensors with similar technology and less depth or breadth. Although these results were unexpected, it bears noting that knowledge depth (when measured as general patent stock) has had inconsistent results in the alliance literature. Colombo et al.(2006) and Rothaermel and Boeker (2008) found patent stock to be positively related to alliance formation, while Stern, Dukerich and Zajac (2014) found it to be the opposite. The search literature may offer an explanation for the negative result found in this study. Katila and Ahuja (2002) found that too much depth will negatively impact inno-vativeness because building on the same knowledge is subject to diminishing returns, and reusing existing knowledge can make an organization rigid and become trapped in an existing technological competency. They also found that too much breadth (or "search scope") reduces innovativeness because the firm's ability to respond to new informa-tion correctly reduces and eventually the costs of integration exceed the benefits of acquiring new knowledge (Laursen and Salter, 2006). It appears that these findings are mirrored in our study in that licensees are less likely to choose patents owned by licensors with strong knowledge depth or breadth (on their own) perhaps due to concerns about their internal rigidity and thin spread of research resources.

In an attempt to better understand the perplexing results for licensor depth and breadth, we add an interaction term composed of the two variables into the analysis. We find that patents owned by licensors with both depth and breadth are more likely to be chosen for a licensing agreement. Using the results in Column 5, the negative effect of li-censor breadth (−23%) is reversed by 9% when paired with a licensee whose average number of citations in the same IPC as the licensed patent increased by 10. These results are consistent with results in the search literature (Katila and Ahuja, 2002) which found that firm depth and breadth are positively related to firm innovativeness through the resulting knowledge uniqueness and absorptive capacity afforded by the mutual reciprocation of the two combined characteristics. In the same way that licensor depth and breadth increase organizational learning and firm innovativeness, they would also combine to increase a licensor's ability to license-out. Technological depth and technological breadth interact with each other to produce a combined balance of knowledge that suits exploratory and problem-solving technology transfer situations (Katila and Ahuja, 2002). This complementary interaction allows firms to create new, unique combinations of

11 For similar empirical approaches see: Herrmann, Kundisch and Rahman (2014) and Foss, Lyngsie, and Zahra (2013).

Table 3. Conditional logit regressions

Variables	Licensors smaller than licensees[a]					Licensors smaller than 75% size of licensee[b]	Licensors smaller than 50% size of licensee[c]
	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
Licensor technological prestige	1.07 (0.016)***			1.06 (0.024)**	1.06 (0.025)***	1.04 (0.034)***	1.08 (0.048)*
Licensor depth	0.14 (0.035)***			0.14 (0.044)***	0.10 (0.036)***	0.08 (0.040)***	0.02 (0.014)***
Licensor breadth	0.73 (0.050)***			0.83 (0.071)**	0.77 (0.079)**	0.74 (0.091)**	0.73 (0.094)**
Licensor breadth* Licensor depth					1.09 (0.043)**	1.16 (0.075)**	1.30 (0.083)***
Licensor size		0.56 (0.039)***		0.85 (0.092)	0.84 (0.094)	0.75 (0.105)**	0.72 (0.128)*
Licensor experience		1.02 (0.015)		1.04 (0.021)**	1.04 (0.020)**	0.94 (0.042)	1.02 (0.049)
Licensor research intensity		0.99 (0.002)**		0.99 (0.005)	0.99 (0.006)	0.99 (0.007)	1.00 (0.009)
Licensor research age		1.10 (0.020)***		1.11 (0.031)***	1.11 (0.032)***	1.15 (0.039)***	1.18 (0.050)***
Past relationships		0.94 (0.131)		0.97 (0.131)	0.98 (0.130)	1.02 (0.258)	2.57 (1.306)*
Patent complexity			1.01 (0.005)	1.01 (0.011)	1.01 (0.011)	1.01 (0.013)	0.98 (0.016)
Patent age			0.22 (0.045)***	0.30 (0.081)***	0.31 (0.082)***	0.11 (0.055)***	0.09 (0.058)***
Patent scope			0.94 (0.065)	0.89 (0.101)	0.88 (0.102)	0.78 (0.132)	0.65 (0.143)**
Patent citations			1.02 (0.005)***	1.02 (0.007)***	1.02 (0.008)***	1.02 (0.010)**	1.03 (0.009)***
Statistics							
Log–Likelihood:	–115.2	–220.4	–192.0	–65.1	–63.7	–47.1	–34.6
Wald Chi-squared:	325.5 (3 d.f.)***	115.1 (5 d.f.)***	171.8 (4 d.f.)***	425.7 (12 d.f.)***	428.4 (13 d.f.)***	349.2 (13 d.f.)***	318.9 (13 d.f.)***
Pseudo R-squared:	0.59	0.21	0.31	0.77	0.77	0.79	0.82
Number of choice groups:	93	93	93	93	93	77	69
Number of observations:	1848	1848	1848	1848	1848	1452	1276

***indicates significance at < 1%, **<5%, *<10%. Odds ratios reported.

a: Mean size of licensees: 7.8, mean size of potential licensors: 4.3, mean size of chosen licensors: 2.1.

b: Mean size of licensees: 7.9, mean size of potential licensors: 2.9, mean size of chosen licensors: 1.1.

c: Mean size of licensees: 8.0, mean size of potential licensors: 1.8, mean size of chosen licensors: 0.7.

knowledge that can be developed and eventually commercialized (Winter, 1984: 293). Thus, the mutual reciprocity afforded by licensor technological depth and breadth make them attractive to licensees who wish to learn from a licensor. In sum, licensor technological depth and breadth combine to produce an ability where the licensor has a balance of both deep and broad knowledge bases that help to expertly and efficiently convey ideas.

The results indicate that patents owned by licensors that have been patenting for a long time (consistent with Ceccagnoli and Jiang, 2013) are more likely to be licensed. We find that newer patents with more patent life remain-ing have a higher chance of being licensed which is in direct contradiction of Ceccagnoli et al. (2010). Perhaps more surprisingly, we do not find any significant connection between two parties having a past relationship and the likeli-hood of a new agreement. This goes against the familiarity principle that has been empirically supported in licensing studies (Kim and Vonortas, 2006a; Kim, 2009) as well as alliance studies (Diestre and Rajagopalan, 2012, Stern et al., 2014). The contradictory results are perhaps explained by the difference in methodologies, where in the previ-ously used pairwise probability method, some partner characteristics in successful alliances were artificially elevated in significance as they were being compared to a large number of unrealistic alliance partners. In terms of patent-level characteristics, we find that those patents with more extensive backwards citations, reflecting innovativeness (consistent with Palomeras, 2007), are more likely to be licensed. Gambardella et al. (2007) found that patents with complexity and scope are more likely to be licensed; however, we find no such significant relationship.

The impact of licensor size on the likelihood of a licensing agreement has had inconsistent results in the literature. Kim (2009) and Kim and Vonortas (2006a) found that larger licensor size leads to higher chances of an agreement, while Gambardella et al. (2007) and Kani and Motohashi (2012) find the opposite. At first, it may appear that our re-sults uphold a negative relationship between licensor size and licensing likelihood; however, since our data set has been selected on the basis of the size relationship between licensee and licensor, we cannot draw too much conclusion from these results. However, the inconsistent results in the literature suggest a complex relationship that we choose to examine more closely. Columns 6 and 7 replicate the model on a smaller sample size where a licensee size relative to potential licensors in each choice group gets progressively larger. Increasing the relative power position of the li-censee over its prospective licensors ensures that licensees face little constraints in their decisions and that a discrete choice model is the appropriate analysis tool for our context (Mindruta et al., 2016). It will also allow us to detect any changes in the attractiveness of licensor attributes as the licensee gains more negotiation strength. Column 5 (and all the other results report in this study unless explicitly stated otherwise) involve licensors smaller in size than the li-censee in their choice group. Column 6 includes only licensors that are smaller than 75% of the size of the licensees in their choice group and Column 7 are for 50% the size. Licensor research age, the combination of licensor breadth and depth and patent age and backwards citations largely retain their appeal as licensee size relative to licensor size increase. Surprisingly, as the size of licensees increase relative to its potential licensors, licensees prefer to license pa-tents owned by increasingly smaller firms and licensees do not appear to find licensor experience or technological prestige as attractive as they did when the licensors were larger. The past relationship between licensor and licensee weakly becomes a determinant of licensing likelihood and licensees increasingly prefer the scope of the patent to be narrow. To sum up, as the size-power dynamic increase in the favor of licensees, they prefer to choose patents and li-censors that are technologically focused with few patents in their area, yet have been researching for a long time. It appears that when licensees are arguably unrestricted with patent choice, they look for patents that will satisfy one particular technical need that is owned by a small but familiar licensor, thus reducing the transaction costs associated with negotiations and probably subsequent payouts.

We offer the model estimated using random effects instead of the fixed effects used in conditional logit as a ro-bustness check in Table 4.[12] One of the advantages of the random effects model is that it easily allows for multiple layers of random effects. Columns 1 and 2 include random effects for each choice group and Column 3 adds a layer of random effects on each individual patent in each choice set to account for latent characteristics such as patent quality. The results are robust to the conditional logit results found in Table 3 and remain remarkably consistent, indicating the lack of latent heterogeneity in the data set.

12 Although a random effects model allows us to include choice-group-specific variables (such as licensee characteris-tics), we choose to estimate the same variables in the condition logit analysis to be consistent and comparabale across both results. Also, the licensse variables do not vary enough across observations to make them reliably estimated.

Table 4. Mixed logit regressions

Variables	Column 1	Column 2	Column 3
Licensor technological prestige	1.03 (0.015) **	1.04 (0.015) ***	1.04 (0.016) **
Licensor depth	0.19 (0.039) ***	0.12 (0.032) ***	0.12 (0.028) ***
Licensor breadth	0.75 (0.046) ***	0.70 (0.054) ***	0.70 (0.052) ***
Licensor breadth * Licensee depth		1.12 (0.034) ***	1.12 (0.032) ***
Licensor size	0.85 (0.065) **	0.86 (0.065) *	0.86 (0.068) *
Licensor experience	1.05 (0.017) ***	1.05 (0.017) ***	1.05 (0.017) ***
Licensor research intensity	0.99 (0.002)	0.99 (0.002)	0.99 (0.002)
Licensor research age	1.12 (0.025) ***	1.13 (0.026) ***	1.13 (0.027) ***
Past relationships	0.92 (0.155)	0.92 (0.074)	0.92 (0.151)
Patent complexity	1.00 (0.008)	1.00 (0.009)	1.00 (0.009)
Patent age	0.23 (0.055) ***	0.22 (0.055) ***	0.22 (0.051) ***
Patent scope	0.98 (0.092)	0.98 (0.095)	0.98 (0.097)
Patent citations	1.02 (0.006) ***	1.02 (0.006) ***	1.02 (0.006) ***
Constant	2.01 (1.021)	2.62 (1.395) *	2.61 (1.432) *
Statistics			
Log-likelihood:	–145.5	–142.7	–145.7
Wald Chi-squared:	131.1 (12 d.f.) ***	118.4 (13 d.f.) ***	167.1 (13 d.f.) ***
Random effects: choice sets	yes	yes	yes
Random effects: patents	no	no	yes

Odds ratios reported.
***indicates significance at < 1%, **<5%, *<10%.
Number of observations: 1848. Number of choice groups: 93.

4. Discussion section

In this article, we explored what determines the likelihood a licensee will choose to in-license a specific patent over other similar patents. From the perspective of licensing propensity, our arguments and results add to prior research focused on how licensor motivations (Arora and Fosfuri, 2003; Fosfuri, 2006; Gambardella et al., 2007; Motohashi, 2008) and licensor capabilities impact their tendency to license-out (Kim and Vonortas, 2006b; Motohashi, 2008; Wuyts and Dutta, 2008; Kani and Motohashi, 2012). By considering the licensor characteristics that lead licensees to choose certain licensors, we make a contribution that also incorporates the demand side of licensing, a perspective that few researchers have studied. We now explain how the findings from our study help scholars and managers bet-ter understand why some patents are selected for a licensing agreement.

4.1 Implications for research

Our findings add to the economics- and capability-based arguments as to why licensors and their patents get chosen. We demonstrate support for the view that licensor prestige increases the likelihood a licensor and its patent will be chosen over other licensors with similar patents. This suggests that licensors emit reputational signals to licensees and that these create what organizational theorists call a “status-based model” of selection (Podolny, 1993). In the con-text of technology licensing, this implies that the market for patented technologies is not just a matter of predicting future revenue streams. It is also influenced by a licensor’s standing in the market, as derived by quality of their prior research outputs. This is interesting as the finding suggests that the standing or prestige of the licensor rather than the quality of its patent alone influences its success in licensing-out.

A second major implication of our study is the provision of an organizational learning explanation for licensing-out success. Our results provide support for the view that experience enhances a licensor’s ability to license-out. This contributes to and extends the concept that licensing-out is a capability where effective licensors accumulate the specific knowledge, people, and routines required to succeed at licensing (Fosfuri, 2006). However, we suggest these resources and their advantages are not only important for being able to license-out but they also play a role in the demand side of licensing by helping licensors to be identified and evaluated by licensees.

Third, our study has theoretical implications for understanding how technological search and technology transfer impact the technology transfer element of a licensor's ability to license-out. There is a well-established optimal licens-ing contract literature (Gallini and Wright, 1990; Beggs, 1992) of which some studies are concerned with how know-ledge transfer affects the terms in a licensing contract (Arora, 1995; Macho-Stadler et al, 1996; Hegde, 2014). These studies focus on the knowledge transfer terms in the agreement contracts and do not consider, to any extent, the char-acteristics of the firms (other than basic size, previous history, and age). Our finding that licensor technological breadth and depth combine to create an environment for effective knowledge transfer contributes to this literature. It shows how this potential knowledge transfer would affect the likelihood of an agreement occurring in the first place. This is an important implication as firms can vary significantly in technological depth and technological breadth, and thus being able to appropriately balance depth and breadth can be vital to licensing success.

Finally, our empirical methodology is also an important contribution. We group each licensee with the patent it licensed and used topic modeling techniques to identify similar licensable patents. This allows for tighter and more controlled analysis than previous models which enlisted a simple binary analysis of the pairings of all known licensees and licensors without regard to technological motivation (e.g., see Kim and Vonortas, 2006a, in the licensing context and Colombo et al., 2006, in the alliance context). By identifying technologically similar patents, we are able to in-corporate the demand side of the licensing transaction which previously had been under-represented in licensing lit-erature (Arora and Gambardella, 2010b). Furthermore, the use of a new methodology encourages us to examine the significance of variables previously thought to influence licensing probability using prior methodologies. In particu-lar, we could not confirm that a previous relationship between a licensor and licensee would contribute to their licensing likelihood, despite the findings from previous studies (Kim and Vonortas, 2006a; Kim, 2009). We did, how-ever, confirm existing evidence that licensors with long patenting history (Ceccagnoli and Jiang, 2013) and patents with extensive backward citations (Palomeras, 2007) are more likely to be licensed.

4.2 Implications for practice

A better understanding of why a particular patent is licensed over other technologically similar patents also has im-portant implications for managers. Our findings suggest a few situations when managers' attention to their own char-acteristics can impact licensing-out success. First, building and maintaining licensor prestige can be a source of licensing-out advantage for licensors. This is because licensees are not just making licensing decisions based on qual-ity of the patented technology, but also on the standing of and technological fit with the licensor. Given that the costs and rewards of licensing can be significant, this finding highlights the importance for licensors to consider the latent value that their prior innovation activities signal to prospective licensees. In addition to producing innovations to en-hance a product portfolio and compete in markets, the quantity and quality of the associated research resources can help to attract future licensing partners.

Second, licensing experience increases a licensor's ability to license-out. Learning-by-doing builds over time and a history of licensing allows firms to acquire knowledge and capabilities that can be utilized in future licensing transac-tions. It may also be possible that proactive licensing-out also involves licensors making themselves known to firms who are active in an appropriate technology field (Solinas, 2015). Driven by such strategies, experienced licensors will have more resources and expertise dedicated to outward licensing, which increases their ability to be known to and selected by potential licensees. As the market for technology becomes more extensive, competitive, and litigious, the costs of searching for, evaluating, and acquiring technologies are also increasing. An awareness of the efficiencies that can be gained via experience, will help smooth the trade in technology.

Finally, balancing licensor technological depth and breadth is important for licensing-out likelihood. Individually, high levels of the two qualities are found to make licensees less likely to choose a licensor's patent for an agreement. Depth is usually thought to be an attractive quality of an alliance partner (Ahuja, 2000); however, in the licensing context, depth reflects research rigidity and evidence of reusing existing knowledge. Similarly, breadth on its own demonstrates a licensor's reduced reliability from spreading its research resources too thin. The results suggest that li-censees anticipate the lack of innovative output which occurs at high levels of depth and breadth individually (Katila and Ahuja, 2002) and choose licensing partners to avoid these issues. That said, the combination of licensor depth and breadth together is an attractive quality to licensees. Licensor technological depth and breadth balance the know-ledge processes for technology transfer transactions and reduce the negative effects of the individual depth and breadth qualities. The two qualities combined act as an attractive signal to prospective licensees that a licensor processes the efficient ability to convey and transmit technical ideas. The post-transaction knowledge transfer is a crucial activity between the two licensing parties (Ceccagnoli and Jiang, 2013) and the attractiveness of both depth and breadth together highlights that licensees are keenly aware of the potential for knowledge transfer when making their licensing choice.

4.3 Limitations and future research

The demand focus of our study and model might imply that licensing is solely about licensees choosing patents but, in reality, licensors choose licensees as much as licensees choose licensors. Although we account for this in the struc-ture of the model, the empirical analysis does not allow for direct verification of it. The formation of a choice set of potential licensees and potential licensor which eventually lead to one particular agreement would be exceedingly dif-ficult.[13] It would be challenging to identify a realistic set of licensees that were interested ex ante in one particular type of technology; the type that was eventually actually licensed.

The determinants were tested on one single industry which is beneficial in that it inherently avoids the complica-tion of between industry differences that could affect partner choice; however, it also lacks empirical verification in other industries. Future research could address this gap, especially focusing on other technology-based industries like chemicals and software. Furthermore, technology licensing is just one mechanism by which firms transfer external knowledge. Consequently, our arguments and approach could also be applied to other forms of technology transfer including the sale of technology (Caviggioli & Ughetto, 2012), inter-firm alliances (Eisenhardt & Schoonhoven, 1996; Gulati et al., 2009), the acquisition of firms (Hayward, 2002; Nadolska & Barkema, 2014) and the role of pa-tent intermediaries: organizations that facilitate the exchange of IP (Hagiu & Yoffie, 2013).

Another limitation of this study is that it does not examine the subsequent success of the licensing deal. The mere attainment of a licensing agreement is only one factor of success in the licensing process. Future research could follow Sakakibara (2010), who made a first step in this direction when she investigated the effect of individual characteris-tics of licensors and licensees on royalty rates and lump sum payments made to licensors.

5. Conclusion

In this article, we set out to understand why some patents get licensed while many others do not. Our fundamental conclusion is that beyond the technological motivation to license-in a patent and the quality of the patent, there are firm-level qualities that can distinguish a licensor from others and these can influence the likelihood that a particular patent will be licensed. At a minimum this incorporation of firm-level status and learning effects allude to the import-ance of sociological mechanisms on licensing probability.

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13 For a different approach to this problem using a matching model, see Mindruta et al. (2014). The pair-wise matching al-gorithm works in the context of licensing but would not address the objective of determining the characteristics of the licensor and patents which are successful compared to other feasible matches.

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Appendix A: Robustness checks

Table A1 reports seven robustness checks on the model. Each changes one aspect of the full model found in Column 5 in Table 3. The results remain remarkably robust across all robustness checks. Columns 1 and 2 change the num-ber of patents in the choice groups to 10 (Column 1) or 30 (Column 2). Although there is a change in the number of observations, the results remain fairly robust. Column 3 disregards potential licensor out-licensing history by ex-panding the pool of available patents to those owned by all potential licensors, even those without any licensing ex-perience. The relaxation of this assumption inflates the choice set of available patents to include those owned by potential licensors who had not licensed out any of its patents in the previous 5 years. There is no way to discern whether the patents owned by those licensors were intended for out-licensing or not. Column 4 does not require the size of a potential licensor to be smaller than the licensee it its choice group. It appears that licensees prefer smaller licensors when licensor size is unrestricted. Column 5 used the 200 topic model to produce the patents in the choice groups.

Column 6 changes the choice sets to include only the patents owned by the chosen licensor. This includes all pa-tents, regardless of the technological area, but only those that were applied for within 5 years before the agreement date. As the firm-level licensor characteristics do not vary between groups, they drop out of the regression. This is a robustness check deliberately crafted to test whether licensees were choosing licensors first and then picking the best of their patents. Column 7 changes the choice sets to include all available biotechnology patents (identified by the four-digit IPC classification used to initially form the pool of patents in the topic modeling technique outlined in Appendix B). This robustness check is intended to confirm whether for the filtering procedure used to identify the technology, similar patents for each licensed patent is more effective than simply using patent-level characteristics which is why only the patent-level characteristics are included. Again, only those patents that were applied for within the 5 years preceding the agreement were included. A comparison of the log-Likelihoods and the R-squared statistics to those for Column 1 of Table 3 confirm that the topic modeling filtering approach adds value and that the model where licensees first choose patents in a particular technical area before licensors is superior.

Appendix B: Topic modeling

Topic modeling was used in this study to narrow down the choice sets of patents. It was necessary because the IPC associated with patents are too broad and subjectively determined by patent examiners (Venugopalan and Rai, 2014). Text analytics offers a more sophisticated method of classifying patents by comparing patents' texts (Wu and Huang, 2010; Gerken and Moehrle, 2012). Recently, Kaplan (2012) and Venugopalan and Rai (2014) applied the sub-branch "topic modelling" to patent classification.

Topic modeling enables us to organize and summarize electronic archives at a scale that would be impossible by human annotation (Blei, 2012). The topic modeling method observes the words in a set of "documents" (in our case, patent abstracts) and seeks to find the topics that could have generated the observed documents (Venugopalan and Rai, 2014). The topic modeling approach used in our study is the simplest one: latent Dirichlet Allocation (LDA).[14] LDA determines the meanings of words by looking at co-presence with other words in the same document or block of text (Blei, Ng & Jordan, 2003). The same word may have different meanings depending on its association with other words in a document (Kaplan, 2012). Topic models surmise a set of topics and identify the words associated with each topic. As each document comprises different topics, the topic modeling algorithm additionally infers the proportion of each topic that constitutes the document (Venugopalan and Rai, 2014).

14 For more formal information about the LDA model, see Appendix B in Venugopalan and Rai (2014), Blei, Ng and Jordan (2003), or Blei (2012).

Table A1. Conditional logit regressions, robustness checks

Variables	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
	10 patents in each choice group	30 patents in each choice group	Licensors do not have to have previous out-licensing history	Licensors not restricted by size relative to licensee	Choice sets made using 200 topic model	Choice sets are all patents owned by chosen licensor	Choice sets are all biotech patents available
Licensor technological prestige	1.08 (0.034) **	1.07 (0.023) ***	1.06 (0.023) ***	1.09 (0.026) ***	1.09 (0.033) ***		
Licensor depth	0.11 (0.047) ***	0.10 (0.034) ***	0.14 (0.042) ***	0.26 (0.062) ***	0.08 (0.031) ***		
Licensor breadth	0.73 (0.094) **	0.78 (0.067) ***	0.76 (0.053) ***	0.73 (0.075) ***	0.77 (0.078) **		
Licensor breadth * Licensor depth	1.09 (0.052) **	1.08 (0.038) **	1.01 (0.028) *	1.06 (0.027) **	1.09 (0.036) **		
Licensor size	0.94 (0.139) *	0.81 (0.077) **	0.86 (0.066) **	0.75 (0.077) ***	0.95 (0.116)		
Licensor experience	1.03 (0.026)	1.05 (0.018) ***	1.05 (0.020) ***	1.03 (0.018)	1.01 (0.021)		
Licensor research intensity	1.00 (0.006)	1.00 (0.005)	1.00 (0.003)	1.00 (0.006)	1.00 (0.007)		
Licensor research age	1.11 (0.050) ***	1.14 (0.031) ***	1.11 (0.025) ***	1.11 (0.031) ***	1.11 (0.034) ***		
Past relationships	0.94 (0.542)	0.98 (0.143)	1.08 (0.111)	1.01 (0.092)	1.03 (0.184)		
Patent complexity	1.00 (0.014)	1.01 (0.010)	1.00 (0.009)	1.00 (0.009)	1.01 (0.011)	0.99 (0.006)	1.01 (0.002) ***
Patent age	0.35 (0.098) ***	0.26 (0.071) ***	0.24 (0.062) ***	0.29 (0.082) ***	0.24 (0.074) ***	0.66 (0.049) ***	0.79 (0.045) ***
Patent scope	0.86 (0.128)	0.89 (0.098)	0.97 (0.100)	0.88 (0.101)	0.92 (0.128)	1.02 (0.084)	1.20 (0.053) ***
Patent citations	1.02 (0.009) ***	1.02 (0.006) ***	1.02 (0.006) ***	1.02 (0.007) ***	1.02 (0.008) ***	1.02 (0.005) ***	1.01 (0.001) ***
Statistics							
Log-likelihood:	–45.4	–78.9	–55.2	–72.4	–56.6	–283.9	–1576.5
Wald Chi-squared:	337.5 (13 d.f.) ***	468.5 (13 d.f.) ***	500.7 (13 d.f.) ***	465.3 (13 d.f.) ***	442.6 (13 d.f.) ***	74.3 (4 d.f.) ***	69.6 (4 d.f.) ***
pseudo R-squared:	0.79	0.75	0.77	0.76	0.79	0.11	0.02
Number of observations:	930	2715	2513	2030	1848	6092	14,843,384
Number of choice groups:	93	93	128	102	93	117	140

***indicates significance at < 1%, **<5%, *<10%. Odds ratios reported.

Potential licensors are smaller than licensee in choice set for all columns except Columns 4, 6, and 7.

Table B1. Abstracts of sample patents

	Patent number	Patent title	Patent abstract	% topic 60	% topic 112
Licensed patent	6623926	Methods for producing 5'-nucleic acid-protein conjugates	Disclosed herein is a method for generating a 5'-nucleic acid-protein conjugate, the method involving: (a) providing a nucleic acid which carries a reactive group at its 5' end; (b) providing a non-derivatized protein; and (c) contacting the nucleic acid and the protein under conditions which allow the reactive group to react with the N-terminus of the protein, thereby forming a 5'-nucleic acid-protein conjugate. Also disclosed herein are 5'-nucleic acid-protein conjugates and methods for their use.	51	27
Most similar patent	6916632	Methods and reagents for molecular cloning	The present invention provides compositions, methods, and kits for covalently linking nucleic acid molecules. The methods include a strand invasion step, and the compositions and kits are useful for performing such methods. For example, a method of covalently linking double stranded (ds) nucleic acid molecules can include contacting a first ds nucleic acid molecule, which has a topoisomerase linked to a 3' terminus of one end and has a single stranded 5' overhang at the same end, with a second ds nucleic acid molecule having a blunt end, such that the 5' overhang can hybridize to a complementary sequence of the blunt end of the second nucleic acid molecule, and the topoisomerase can covalently link the ds nucleic acid molecules. The methods are simpler and more efficient than previous methods for covalently linking nucleic acid sequences, and the compositions and kits facilitate practicing the methods, including methods of directionally linking two or more ds nucleic acid molecules.	84	11

The first step in this method was identifying the relevant patents for which the topic modeling approach will be applied. The pool of patents had to be from the broadest technological area and yet still pertain to biotechnology. We noted the four-digit IPC of the licensed patents and then gathered all the patents in the NBER database in those same categories (A01N, A61B, A61F, A61K, A61M, A61N, A61P, B05B, C07C, C07D, C07H, C07K, C12N, C12P, C12Q, F21V, G01N, Q61K). There were over 90,000 patents that were granted between 1988 (5 years before first agreement in our data set) and 2007 in these 18 categories.

The abstracts for all the relevant patents were assembled and the topic modeling software (MALLET) identified an initial set of topics.[15] The top words associated with the initial set of topics showed a number of "stop words" (such as "the," "or," "and") which were removed in subsequent analyses. MALLET requires that we pre-set the number of topics in the database. We experimented with 100, 200, and 500 topics. After doing some careful comparison of

15 We used MALLET software as it is actively updated and used in current literature (for examples, which has used MALLET: Venugopalan and Rai 2014 and Thomas, Adams, Hassan and Blostein 2014).

Table B2. Top 20 terms associated with topics 60 and 112

Topic 60	Nucleic	Invention	Acid	Proteins	Molecules	Methods	Vectors	Cells	Sequences	Expression
	Polypeptides	Host	Isolated	Recombinant	Provided	Encoding	Acids	Compositions	Disclosed	Antibodies
Topic 112	Nucleic	Acid	Amplification	DNA	Target	Sequence	Reaction	Primer	Polymerase	Invention
	Methods	Sequences	Sample	Method	Detection	Primers	Chain	Nucleotide	Sequencing	Present

similar patents, we found that 100 and 200 topics were far too broadly defined and not useful for our purposes. The 500 topic model performed well on random checks of the patents. We used the 500 topic model as the default for our data analysis; however, we offer the 200-topic model as a robustness check in Table A1.

The algorithm then produces a vector of weights of each topic in each patent abstract. Patents may contain several topics, though of different weights. We used the KL divergence formula (Bigi, 2003; Pinto *et al.*, 2007) to determine the similarity of each licensed patent to each possible patent from the relevant pool determined earlier. The KL divergence of the probability distributions P, Q on a finite set X is defined as shown in the following equation[16]:

$$D_{KL}(P||Q) = \sum_{x \in X} P(x) \log \frac{P(x)}{Q(x)}.$$

The KL distance is symmetric and is derived from the KL divergence:

$$D_{KLD}(P||Q) = D_{KL}(P||Q) + D_{KL}(Q||P).$$

The KL distance measures how similar each patent's distribution of applicable topics are to each other and, in our data set, ranges from close to 0 (very similar) to 15 (very different). Table B1 shows the abstracts of a sample licensed patent and its most similar patent along with the percentage distribution in their two dominant topics. Table B2 displays the top 20 terms associated with the two topics.

Each choice set is composed of the top 19 most similar patents to the licensed patent in the choice set using the KL distance metric and the licensed patent itself, totaling 20 patents. We offer robustness checks where choice sets have 10 or 30 patents each in Table A1.

16 KL distance has been used in many natural language applications like query expansion (Carpineto, Mori, Romano and Bigi 2001), language models (Bigi, Huang and Mori 2003), and statistical language modeling (Dagan, Lee and Pereira 1999).