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Does licensing-out lead to improved learning for the licensor?

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Abstract

While the learning effects from licensing to the licensee have been studied extensively, this paper aims to investigate whether out-licensing also has an 'outside-in' nature, whereby the licensor – who typically has to interact with the licensee in order to permit effective use of the out-licensed technology – also learns from this interaction. To answer this question, we analyze a cross-sectional dataset with 255 unique licensing agreements between 1995 and 2003. We operationalize learning by measuring backward citations from licensor to licensee subsequent to a deal. Preliminary results show that engaging in licensing is positively related to the number of times licensors cite patents by their licensees, suggesting the possibility of a learning effect to the licensor.

Jelcodes:O32,O31

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Abstract

While the learning effects from licensing to the licensee have been studied extensively, this paper aims to investigate whether out-licensing also has an 'outside-in' nature, whereby the licensor – who typically has to interact with the licensee in order to permit effective use of the out-licensed technology – also learns from this interaction. To answer this question, we analyze a cross-sectional dataset with 255 unique licensing agreements in the pharmaceutical industry between 1995 and 2003. Controlling for technological and geographical distance, preliminary results show evidence of learning by licensors from licensees, measured by patent citations after the licensing deal.

Keywords: technology licensing, innovative performance

Jelcodes: O31; 032

1. Introduction

The last few decades have witnessed a rapid growth of licensing as a means to transfer technology between two firms. This is especially true for high-tech industries such as semiconductors, chemicals, electronics, but also pharma and biotech – industries that are characterized by large investments in R&D and high rates of patenting activity (Arora et al., 2001). Within these industries, companies frequently engage in out-licensing in order to capitalize on their R&D efforts (Arora & Fosfuri, 2003), and licensing revenues represent a considerable amount of their profits (Fosfuri, 2006). A prime example in this respect is IBM, who increased their licensing income in the 1990s from USD 30 million to USD 1 billion by systematically identifying and out-licensing their technology (Rivette & Kline, 2000).

However, the benefits of technology licensing go further than just realizing extra cash from out-licensing. In particular, the learning aspect of licensing has been studied widely over the last years. So far, the available literature has especially shed light on the learning effects to the licensee. Technology in-licensing may create value by allowing the firm to tap into external knowledge originating from the R&D efforts of other firms (Arora et al., 2001; Athreye & Cantwell, 2007). Moreover, several studies have highlighted the learning effects of in-licensing (i.e. Johnson, 2002; Arora & Ceccagnoli, 2006; Leone et al., 2015). For instance, it is shown that by licensing in technologies that are developed outside the organization, firms can increase the diversity of their technology portfolio and may ultimately improve their ability to innovate. Technology licensing furthermore allows firms to speed up the development of new innovations by sourcing in external knowledge (Leone & Reichstein, 2012; Leten et al., 2013), which is important to generate first-mover advantages in the market place (Langerak & Hultink, 2006).

While the learning effects of in-licensing have gained a lot of attention in the recent literature, surprisingly little empirical research has been conducted on whether out-licensing also has an 'outside-in' nature, whereby the licensor – who typically has to interact with the licensee in order to permit effective use of the out-licensed technology – also learns from this interaction. One notable exception, and by our best knowledge the only one so far, is the study by Srivastava & Wang (2015), who empirically show that a licensor is capable of improving its future patent filing propensity as a result of spill-over effects stemming from the interaction with the licensee. The goal of our paper is to generate more insight in this mechanism by identifying more directly whether licensors learn from licensees. More specifically, we investigate whether engaging in licensing-out with a partner generates more backward citations to the technologies of the licensee, which we see as a possible indication of a knowledge flow from the licensee back to the licensor.

The reason why we think it is worthwhile to study the learning effects of out-licensing to the licensor, is that – in a licensing agreement – the licensor often not only transfers its knowledge to the licensee, but furthermore engages in offering guidance to the licensee in order to effectively implement the licensed technology. There might be a flow-back of knowledge, for instance on new fields of application of its licensed technology.

2. Data

In order to study the impact of licensing-out on knowledge flow-back to the licensor, we set up a dataset with information on 255 unique licensing deals of 159 firms active in the pharmaceutical and biotech industry. Firms in our sample have their headquarters in either the EU, the US or Japan. The selected firms were among the top R&D spenders in the industry, as identified by the 2004 EU Industrial R&D Investment Scoreboard, which ranks the top 1,500 R&D investors in the world. We observe our sample in a 9-year time frame (1995-2003). In our empirical analyses, we study learning effects of out-licensing to the licensor by adopting a dyad setup. We start by identifying license agreements between two firms that are both part of our sample of 159 firms, giving us the 255 unique licensing deals. In a next step, to find counterfactual cases in order to isolate the effect of out-licensing, for each of these 255 deals we randomly sample ten dyads of two firms in our sample of 159 firms who have no licensing agreement with each other for that given year. While taking the random sample of

10 counterfactual cases per deal, we hold our licensor in that deal for which we sample counterfactuals constant.

Our data is collected at the consolidated level, which means that we take into account the licensing agreements and patent data of parent firms as well as their consolidated (majority-owned) subsidiaries in order to assess the number of licensing agreements and the number of backward citations from licensor to licensee. In line with prior work by Leten et al. (2007), we make use of yearly lists of subsidiaries included in annual reports, as well as yearly 10-K reports filed with the SEC in the US. Specifically for the Japanese firms in our sample, we furthermore use information on foreign subsidiaries published by Toyo Keizai in the yearly Directories of Japanese Overseas Investments. As there might be considerable changes in group structures of parent firms over time (due to M&A activity or spin-offs), the consolidation exercise has been performed on a yearly basis. The motivation for performing the consolidation lies in the fact that both patenting activity and licensing is often performed on the level of the subsidiary. Magerman et al. (2005) estimate that on average 20 percent of the patents in a parent's patent portfolio is applied for under either a subsidiary's name or a different name than the current name of the parent firm.

a. Patent data and the dependent variable

Dependent variable: Number of backward patent citations

We make use of patent citations as an indicator for knowledge spillovers between firms. More specifically, we approximate learning effects to the licensor by aggregating backward citations from the licensee to the licensor within a dyad. Although the literature recognizes the difficulties in observing knowledge flows (Jaffe et al., 1993), patent citations have widely been used as a measure of knowledge flows from firm to firm (Almeida & Kogut, 1999; Rosenkopf & Nerkar, 2001; Singh & Agrawal, 2011). Following Roach & Cohen (2013), we recognize several advantages of using patent data to measure knowledge flows: (1) there is a wide coverage across firms, as well as (2) an extensive coverage over time, and (3) they are freely and easily available from different sources, such as the US

Patent Office (USPTO), the European Patent Office (EPO) or the NBER patent database (Hall et al., 2001). Disadvantages that come with the use of patent citation data include the potentially considerable number of citations added by patent examiners, possibly diluting the actual size of knowledge flow from citing to cited firm (Alcacer & Gittelman, 2006) and the suggestion that patent citations may perhaps be noisy measures of knowledge flows (Jaffe et al., 1998; Agrawal & Henderson, 2002). Since our dependent variable is essentially a count of backward patent citations and therefore only takes discrete non-negative values, we employ a negative binomial model.

To construct our measure of backward citations from licensor to licensee, as well as several of our control variables, we use data from PATSTAT for the patent families related to our list of parent firms and their subsidiary firms. We obtain data on harmonized names of the filing companies, the application year, patent citations, the technology classification (using the International Patent Classifications (IPC) assigned by patent examiners to each patent) and inventor names.

Independent variable: 5-year stock of licensing agreements

Our independent variable consists of a stock of licensing agreements between a pair of firms for a given year *t*. We gather this information on licensing agreements from the Thompson Reuters RECAP database, which includes licensing contracts and other forms of collaborations between firms for the pharmaceutical and biotech industry. Licensing agreements are observed by taking a moving time window of 5 years. Our independent variable therefore is a stock of licensing deals that took place in the past 5 years between a licensor and a licensee. The choice to work with a five year moving time window is motivated by the opportunity of a more reliable measurement of learning that it offers. It recognizes the fact that, subsequent to a licensing agreement, it might take some adaptation time before actual learning from the licensee back to the licensor will happen.

b. Control variables

Technological similarity

We calculate a measure of technological similarity between firms in a dyad to get a view on the degree of technological overlap between both firms' patent portfolios as well as the distance of the technologies that these firms have patented in. The rationale behind this measure is that we expect that – as firms are more closely related to one another in terms of technological overlap – this will be an important driver for backward citations between this pair of firms. We measure technological similarity using an angular separation (or cosine distance) measure, which was first coined in the literature by Jaffe (1986). This cosine distance measures to what extent both firms' vectors point in the same direction, whilst adjusting for the vector's length. The technological similarity between the patent portfolios of firm *i* and firm *j* is given by:

$$Technological\ similarity = \frac{F_i' F_j}{\sqrt{F_i}\,\sqrt{F_j}}\ , \tag{1}$$

where F_i represents the *i-th* row of *F*, representing firm *i*'s technology profile.

In measuring this variable, we have started from the IPC-classes of firms' patent portfolios. More specifically, we take into consideration all IPC-classes of all new patent applications of firms within our dyads in the last 5 years. Taking only the last 5 years has the advantage that it recognizes the fact that firms' R&D activities (and therefore their patent applications) are dynamic and may shift over time, for instance due to focus on new fields of applications. For this reason, we also calculate this measure on a yearly basis for all firms that make up the dyads in our dataset. The technological similarity measure takes the value 1 in case of a perfect overlap between both firms' technology profile, while it approaches zero as firms' technology profiles share less IPC-classes. In this study, we take two levels of IPC into account. First, we designed a technological similarity measure on IPC-3 level, which represents 639 subclasses. As we want to test whether this degree of technology classification is too general, we also take a similarity measure on IPC-4 level, which represents 7314 main groups and is one level deeper down the classification hierarchy than our IPC-3 measure.

Geographical distance

Similarly to technological distance between firms' parent portfolios, we also create a measure for the geographical distance between their patent portfolios. We expect this measure to be relevant because the more geographically near inventors of both firms in the dyad are, the more opportunities they have to physically meet and collaborate with each other, creating an additional channel for learning besides licensing. We obtain the data for this measure from REGPAT, which is a database maintained by the OECD listing the company- and inventor addresses linked to a NUTS-level 3 code for approximately 14 million EPO- and PCT-patents. NUTS (Nomenclature of Territorial Units for Statistics) is a hierarchically designed classification system which divides up the EU territory on different levels. NUTS-3 is the most detailed level of division, focusing on small regions.

The geographical distance between the patent portfolios of two firms is calculated analogous to the technological similarity measure that we introduced above, by taking the cosine measure of all NUTS-3 classes of all new patent applications of firms within our dyads in the last 5 years. Geographical distance between two firms' patent portfolios is measured on a yearly basis using a 5-year rolling-forward time window, and is calculated as:

$$Geographical\ distance = \frac{G_i' G_j}{\sqrt{G_i}\ \sqrt{G_j}}\ , \tag{2}$$

where G_i represents the *i* th row of *G*, representing firm *i*'s geographical distribution matrix.

Controlling for firm size

To control for firm size of the licensor and the licensee, we use the aggregated number of patent applications within the last 5 years. We expect firms with a larger amount of patent applications to be more likely to cite its licensing partner. To smooth the distribution and correct for extreme outliers, we take a log-transformation of our measure for firm size.

3. Empirical Results

a. Descriptive statistics

Figure 1 shows the distribution of the number of unique licensing agreements between two firms in our sample of 159 R&D-intensive firms over the years that we observe. We see that there is an upward trend in the number of licensing deals over our years, which corresponds with the literature stating that licensing has gained in importance to firms over the last decades (Arora et al., 2001). As these licensing agreements are – depending on the year in our sample in which they are signed – sampled between one and maximum 5 consecutive years, the number of observations for our 5-year licensing stock amounts to 988 observations. For each of these observations we have 10 counterfactual cases, bringing our total number of observations to 10,686. This explains the very skewed distribution of the value of our licensing stock of 5 years (shown in Figure 2), as the zero-values are these counterfactual cases which make up 90% of our total observations. Looking at Figure 3, which shows a quantile distribution of the number of backward citations from licensor to licensee, we can see that between the vast majority of firms in the dyads in our dataset, there are zero backward citations. This highly skewed distribution of the variable of interest calls for an appropriate empirical approach, as normality in the distribution of this variable can clearly not be assumed. Furthermore, our dependent variable – being a count measure of backward citations – is discrete in nature. For these reasons, we opt to work with a negative binomial regression throughout our analyses. The correlations between our variables of interest and the control variables are shown in Table 3. The low correlation scores between our independent variables suggest that collinearity should not be an issue in this set-up.

b. Multivariate analysis

Results of the negative binomial regression models predicting the number of backward citations are reported in Table 4. The results in the first and second column include a technological similarity measure based on the IPC-3 codes of both firms' patent stock in years *t-5* until *t-1*, whilst the technological similarity measure included in columns (3) and (4) is based on the IPC-4 codes, also in a 5-year time window. The results in columns (1) and (3) include control variables only. In column (2) and (4) we add our variable of interest.

The results in both estimated models support our hypothesis. Firms engaging in licensing-out have a higher likelihood of citing the patents of their licensee more frequently subsequent to the licensing agreement. Note that the coefficients become slightly smaller when we include technological similarity measured on IPC-3 level instead of IPC-4, suggesting that a closer technological relatedness between two firms adds to the learning effect. Furthermore, we argue that both our controls for technological similarity as well as our control for geographical distance (or proximity) seem to pick up important determinants for the likelihood of a licensor to cite its licensee, subsequent to a license agreement.

4. Conclusion and Discussion

In this article we aimed to investigate whether out-licensing entailed an 'outside-in' nature, by which the licensor benefits from the interaction with the licensee following a license agreement in terms of learning. We measured learning as the number of backward citations from the licensor to patents of the licensee, in the years after the deal. To analyze this research question, we developed a cross-sectional dataset containing 255 licensing agreements between 1995 and 2003. (Very) preliminary findings seem to suggest that there indeed is a positive relationship between being involved in licensing-out and subsequent citations to the licensing partner.

Although these first results offer an incentive to empirically dig deeper into our research question, we acknowledge some potential shortcomings in the current set-up, and outline some further steps here on how we aim to remediate these in the future. First of all, in our current set-up we randomly sample 10 counterfactual dyads in which the firms do not engage in any licensing deals in the 5-year stock for a given year. While this set-up in principle does not introduce any bias since it doesn't favor the selection of counterfactual partners from whom the licensor is very unlikely to learn, we will check the robustness of our findings through a matching approach. Second, we want to include several new control variables, both at the dyad level as at the licensor-level. Specifically, we will include other forms of collaborations between dyad partners, such as alliances and co-development. Controlling for these collaborations between firms will further help to rule out a 'hidden treatment' from licensing. This data can also be obtained through the RECAP database that we use to extract information related to technology licensing. An additional source that we aim to include is alliance-related data from the SDC Platinum database, which contains data on alliance deals for the period 1962-2009. Finally, we will include interaction effects on our variables, in order to account for possible moderating effects on our variable of interest.

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Tables and Figures

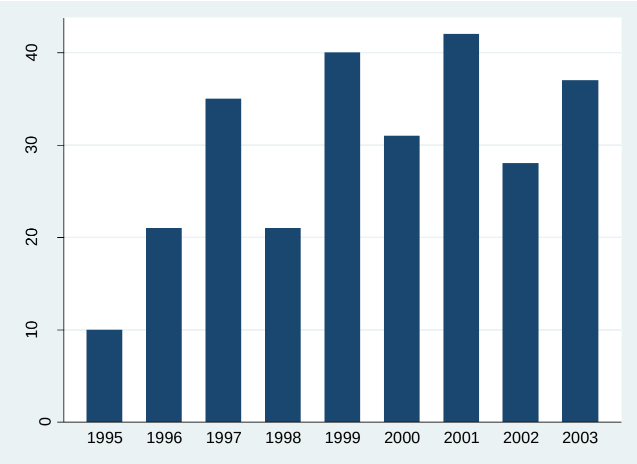

Figure 1: *Distribution of number of unique deals by year (n= 265)*

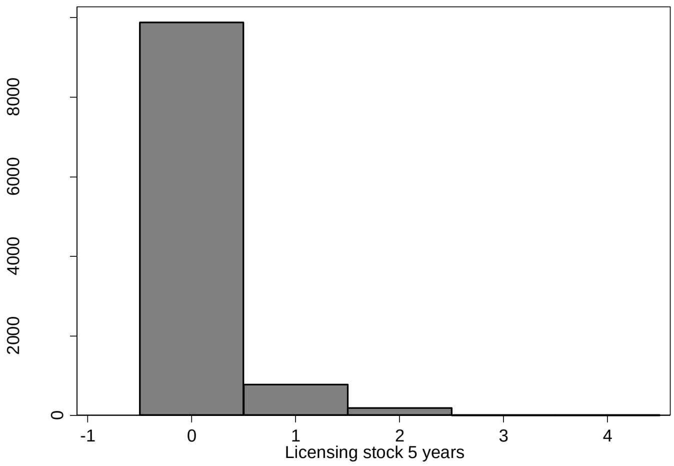

Figure 2*: Licensing stock 5 years; distribution of number of deals per stock*

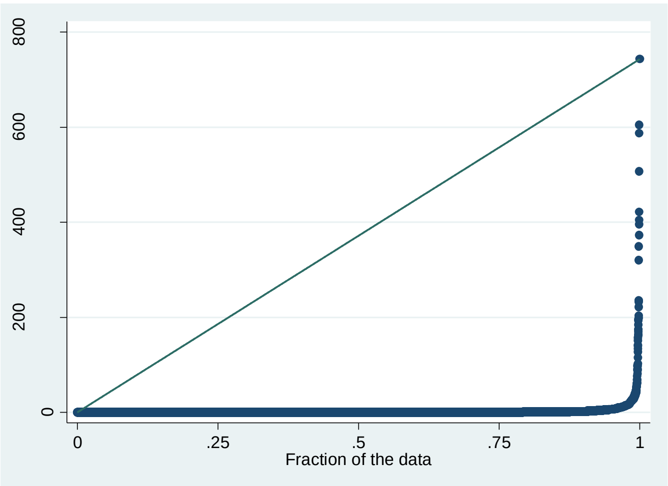

Figure 3: *Quantile distribution of Number Backward Citations*

Variable	Full description
Dependent	
Number backward citations	Number of backward citations from licensee to licensor, measured in year *t*.
Independent	
Licensing stock 5 years	5-year stock of licensing agreements on dyad level, measured in years *[t-5; t-1]*.
Controls	
Number patents licensor 5 years	The 5-year stock of patent applications of the licensor, calculated as the aggregate of patent applications in year *[t-5; t-1].* We log-transform these values, as log(1 + number patents licensee 5 years).
Number patents licensee 5 years	The 5-year stock of patent applications of the licensee, calculated as the aggregate of patent applications in year *[t-5; t-1].* We log-transform these values, as log(1 + number patents licensee 5 years).
Technological similarity IPC-3	Cosine distance measure calculated on dyad level, based on the IPC-3 codes of both firms' patent stock in year *[t-5; t-1].*
Technological similarity IPC-4	Cosine distance measure calculated on dyad level, based on the IPC-4 codes of both firms' patent stock in year *[t-5; t-1].*
Geographical distance	Cosine distance measure calculated on dyad level, based on NUTS-3 codes of inventor addresses listed in firms' new patent applications. The measure is calculated on both firms' patent stock in year *[t-5; t-1].*
IPC-3 missing	Dummy variable to account for cases where the technological similarity at IPC-3 level could not be calculated.
IPC-4 missing	Dummy variable to account for cases where the technological similarity at IPC-4 level could not be calculated.
Geographical distance missing	Dummy variable to account for cases where the geographical distance between firms' patent portfolios on NUTS-3 level could not be calculated.

Table 1: List of variables

Variable	N	Mean	Std. Dev.
Number backward citations	10,868	1.973408	17.52651
Licensing stock 5 years	10,868	.1128082	.3884427
Number patents licensor 5 years	10,868	481.1377	870.5863
Number patents licensee 5 years	10,868	402.3497	752.3687
Log number patents licensor 5 years	10,868	4.734105	1.805117
Log number patents licensee 5 years	10,868	4.498092	1.896338
Technological similarity IPC-3	10,868	.587077	.2916436
echnological similarity IPC-4	10,868	.4255775	.2825035
Geographical distance	10,868	.0585039	.1501395
IPC-3 missing	10,868	.0537357	.2255058
IPC-4 missing	10,868	.0553	.2285753
Geographical distance missing	10,868	.2773279	.4477003

Table 2: Descriptive statistics

	1	2	3	4	5	6	7	8	9	10	11	12
1. Number backward citations	1.0000											
2. Licensing stock 5 years	0.1456*	1.0000										
3. Number patents licensor 5 years	0.1549*	-0.0043	1.0000									
4. Number patents licensee 5 years	0.1913*	0.3035*	-0.0163*	1.0000								
5. Log number patents licensor 5 years	0.1248*	-0.0049	0.7714*	-0.0010	1.0000							
6. Log number patents licensor 5 years	0.1458*	0.2511*	-0.0124	0.7331*	0.0036	1.0000						
7. Technological similarity IPC-3	-0.0374*	0.0618*	0.1654*	0.1518*	0.2073*	0.2589*	1.0000					
8. Technological similarity IPC-4	0.0048	0.0885*	0.2102*	0.1696*	0.2449*	0.2930*	0.8504*	1.0000				
9. Geographical distance	0.0398*	0.0839*	0.0051	0.0317*	0.0366*	0.0631*	0.0613*	0.0987*	1.0000			
10. IPC-3 missing	0.1851*	0.0474*	-0.0422*	-0.0617*	-0.2355*	-0.2645*	-0.4797*	-0.3590*	-0.0929*	1.0000		
11. IPC-4 missing	0.1818*	0.0448*	-0.0440*	-0.0644*	-0.2347*	-0.2694*	-0.4852*	-0.3645*	-0.0939*	0.9849*	1.0000	
12. Geographical distance missing	0.0385*	-0.1027*	-0.2244*	-0.2279*	-0.3405*	-0.3986*	-0.2831*	-0.3156*	-0.2414*	0.3847*	0.3897*	1.0000

*Significance of correlations is indicated by * (0.01)*

Table 3: Correlation matrix

Variables	(1)	(2)	(3)	(4)
Licensing stock 5 years		0.486 (0.130)***		0.536 (0.132)***
Log number patents licensor 5 years	0.468 (0.047)***	0.481 (0.044)***	0.441 (0.050)***	0.455 (0.046)***
Log number patents licensee 5 years	0.677 (0.048)***	0.645 (0.049)***	0.672 (0.047)***	0.635 (0.047)***
Technological similarity IPC-3	2.248 (0.321)***	2.262 (0.313)***		
IPC-3 missing	6.111 (0.324)***	5.993 (0.326)***		
Technological similarity IPC-4			2.358 (0.348)***	2.416 (0.341)***
IPC-4 missing			5.664 (0.323)***	5.548 (0.328)***
Geographical distance	2.295 (0.330)***	2.209 (0.352)***	2.055 (0.302)***	1.955 (0.324)***
Geographical distance missing	-0.846 (0.262)**	-0.780 (0.269)**	-0.783 (0.259)**	-0.709 (0.266)**
Constant	-8.318 (0.403)***	-8.315 (0.369)***	-7.863 (0.399)***	-7.870 (0.362)***
lnalpha	1.064 (0.135)***	1.057 (0.131)***	1.050 (0.135)***	1.041 (0.129)***
Pseudo-R^2	0.20	0.20	0.20	0.21
N	10,868	10,868	10,868	10,868
Log Likelihood	-9,236.44	-9,196.22	-9,190.79	-9,140.40
Chi2	TBA	TBA	TBA	TBA

Significance indicated by: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 4: Results of negative binomial regression analysis of Number backward citations