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University Research and Technology Transfer A Competing Risks Approach

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Abstract
The paper uses a competing risk approach to characterize the process of transferring technology from University of California, San Diego to start-up and established firms. Licensing technology is formalized in my proposed framework as a mechanism in which both types of firms compete to license a given invention. The main purpose of the analysis is to identify the differences between the two processes: start-up licensing process and established firm licensing process. These differences refer to the quality of technology licensed by the two types of firm and the speed of licensing the technologies after disclosure.In addition, the methodology and results of the paper provide a deeper understanding of the managerial decisions of firm creation and can help policymakers at the state and federal level design commercialization and licensing policies that can lead to a successful commercialization of inventions with beneficial impact on consumers and society overall. The empirical analysis uses a unique panel data set obtained from the Technology Transfer & Intellectual Property Services at University of California at San Diego[1], consisting of 406 cases of invention disclosures between1971-2003[2]. Start-up firms are firms founded on the basis of inventions licensed from UCSD by the scientific inventors of the respective inventions. Inventor-founded firms are arguably better match for the respective inventions due to the informational advantage of the founders in the use of the technology licensed.The results show that start-up firms generally license the inventions faster than the established firms, due to the asymmetric information about the potential value of the invention. In addition, estimates of the quality characteristics of inventions bring evidence that start-up firms license higher quality inventions than established firms.
Key words: start-ups, competing risks, licensing, university research, citations, secrecies

1. Introduction and Motivation

Universities increased their role in the technology transfer to the industry sector over the last two decades[3]. The research activity and innovative output of universities have an impact on the real economy (employment, output, productivity) with important implications at the level of firms and industry, see Encaoua D., Hall H.B, Laisney F and Mairesse J (2000).

There has been a an important body of economic literature focusing on understanding various aspects concerning the contribution of universities to technological growth: the role of incentives put in place by universities in stimulating the research activity, designing optimal licensing contract, and studying the relationship between the probability of license and characteristics of inventions. For example, Feller I. (1990) discussing various licensing strategies used by eh Technology Offices at universities and their impact on research output and commercialization of inventions, including equity holdings by the universities in newly created start-ups. Other articles, like Powers, Joshua B.; Campbell, Eric G.(2009) discuss the need for universities to use their most valuable assets – patents and intellectual property – as a tool to promote local and national economic growth.

University research has economic implications through two important channels: spillovers and direct licensing of technology. Adam B. Jaffe (1989) and Jaffe, Trajtenberg&Henderson (1993) are two examples of studies on spillover mechanism. The first paper quantifies the effect of R&D of one firm on the other firms (using proximity of firm's patents in technological space) while the other paper brings evidence that knowledge spillovers are geographically localized.

The motivation of my paper heavily draws from the literature on licensing technology and optimal contract. One of the most important elements of my analysis is to build a strong microeconomic foundation of the licensing process. This is achieved by implementing an optimal structure of incentives for the inventor and licensee.

Numerous studies focused on the contractual relationship between inventor and licensee and the role of asymmetric information in licensing university technology.

Arora (1996) analyses the importance tacit knowledge in contracting technology. In his model, contracting for know-how is very difficult due to double-moral hazard problem. In particular, the inventor might not provide enough effort to help the licensee to further develop the technology, and there is threat that licensee might appropriate the technology after the inventor transferred enough know-how to licensee. Solutions to make the contracts more efficient are the use of output-based royalties, reputation building though repetition or the inventor can tie the transfer and payment of know-how to a complementary input (whose transfer is easy to monitor).

Jensen&Thursby (2001), using a recent survey of US universities, find that majority of university technology is licensed at early stages. The licensee needs the inventor's input to further develop the technology and in order to mitigate the moral hazard problem the inventor needs to be provided with royalties and/or equity in the licensee firm[4].

An interesting study on the effect of university incentives on academic research is Schankerman (2003). The author examines how the share of license royalties provided to inventors affects the number and licensing value of inventions. The paper finds that inventors clearly respond to the incentives: the higher the royalty shares to academic scientists the more inventions and license revenues are generated.

Munteanu (2012) also showed, using a data set from UC San Diego,that the probability of licensing depends on the stage of development of inventions. This is a key finding that can help us develop a more comprehensive approach to the licensing process.

Finally, Lowe A. Robert (2002) suggests a model in which the information asymmetry between inventor and outside firm raises the cost of licensing the technology[5]. Inventors then choose to found start-up firms to license their own technology, to further develop them and reduce the asymmetry in information.

Obviously, there are weaknesses and areas of improvement in the approaches described above. My research on licensing technology at UC, San Diego and the data available from the campus suggest a different incentive mechanism at the level of inventor. This has implication on the existing theories on the formation of inventor-founder firms and characteristics of technology diffusion through START-UP and ESTABLISHED firms. I plan to address some of these weaknesses by proposing a more unified approach to licensing process, with a stronger microeconomic foundation with respect to inventor's incentives and the role of asymmetric information in technology transfer through inventor-founder firms.

My paper uses some of the features of the competing risk model from Thursby (2003) to formalize the licensing process at University of California, San Diego.

The main contribution of the paper is to propose a different analytical framework of analyzing the licensing process and offers a new explanation for the formation of inventor-founder firms. In addition, I estimate the effect of various measures of invention's quality on the likelihood of invention being licensed.

In contrast to Lowe (2003), I model the formation of start-up as a result of inventor's utility maximizing behavior and not as a result of high cost of licensing by established firms. Thus, licensing own inventions through start-up firms can be described as a result of inventor's utility maximizing behavior. My data set and interviews with people involved in the technology transfer process suggests that this is a more accurate description of the licensing process by START-UPs[6].

The main questions I would like to answer in my paper are: Are the high quality inventions licensed faster than lower quality inventions? Do START-UP firms license higher quality inventions than ESTABLISHED firms due to asymmetric information about the technology?

In my framework, at every moment in time, each invention is at the risk of being licensed by two types of firms: start-ups or established firms. Both types of firms, before licensing the technology, try to learn about the potential value of the invention for the firm (or determine the value of the match). The firm that forms the best match with the invention, license the technology first (if any).

I use a competing risks method similar to Thursby(2003) to show that there are differences in the quality of technology licensed and the speed of licensing for two types of firms: START-UP and ESTABLISHED firms.

Specifically, before licensing the technology, the firms have the option of signing a secrecy agreement. The secrecy agreements allows a potential license access determine if they are interested in using a given invention.

Start-up firm are founded on the basis of technology licensed from university AND the founder of the firm is the scientific inventor of the technology licensed. A priori, inventor-founder firms have more information about a given technology than an established firm.

I show that there is substantial variation in the number and timing of secrecy agreements, and use this variation to estimate the effect of the *number of agreements* executed and other covariates describing the quality of invention on the probability of being licensed by the two types of firms.

This paper makes two main contributions. First, it proposes a new methodology of describing and estimating the likelihood of the first license for a given invention. This approach incorporates, as opposed to previous models in the literature, the dynamic process of updating beliefs about the underlying value of the invention by the potential licensees. For every potential licensee, the list of previous agreements executed (SECRECY) on the license is informative about the quality of invention and can be used to update the initial beliefs about the quality of the match.

Second, I show that the number of secrecies executed on the invention until the first license is issued have a smaller impact on probability of license by a START-UP firm than on the probability of license by an ESTABLISHED firm.

The paper is organized as follows. Section 2 offers a detailed description of the data set. In Section 3, I propose a basic theoretical model formalizing the licensing mechanism. Section 4 describes the empirical methodology used in estimation and the results. Finally, Section 5 summarizes the main results and includes direction for further research.

1.1 Data Set Description

Before I describe the data set, I would like to mention first the main phases involved in licensing university technologies. The sequence of steps involved until the first license is issued (if any) plays a very important role in constructing my theoretical model and interpreting the results.

Stage1 Having received a disclosure (invention), UCSD TechTIPS[7] office makes a thorough analysis of the technology to determine suitable ways for protection and marketing[8]. Nonconfidential disclosures are used to approach suitable licensees that are willing to develop the technology.

Stage2 Short-term agreements, SECRECIES, are used executed and allows a potential licenses access to more detailed information about the technology. These agreements help the firm in deciding if it is further interested in pursuing the technology.

Stage3 Letter and options agreements are used show the firm's intent to negotiate a license and allow a more in depth evaluation of technology.

Stage 4 A license agreement is signed for the use of technology in exchange of a fee and royalty payments if the products are commercialized.

The data set was constructed from two sources. The most important part of the data set was provided by the TechTips Office at UC San Diego and it consists of records of all inventions disclosed at UCSD campus between 1971-2003 for which there was at least one agreement executed (SECRECY, or LICENSE).

A typical record for a given invention displays the following information: case number, life-to-date receipts and life-to-date expenses, name of inventor(s), invention short title, disclosure date, patent application date, patent number (if any) and patent expiration date.

In addition to these elements, every invention record presents a history of all agreements executed on that invention since disclosure.

For a particular invention, the history of agreements has the following format:

Control #	*Stat*	*Comp*	*AgrType*	*Effective/ Executed*	*First Sale*	*Last Royalty*
19xx-yy	AS	ZZZZ	SECR	02/01/95	02/09/95	
19vv-mm	AS	PPPP	SECR	09/07/99	09/08/99	mm/dd/yy
19uu-ff	AL	SSSS	LNEX	01/12/01	01/12/01	mm/dd/yy

From the list of agreements of a given invention I can identify: the status of the agreement (active or terminated), date of agreements, name of the licensee and type of license (EXCLUSIVE or NON-EXCLUSIVE).

In addition to invention's licensing records, UCSD TechTIPS kindly provided me a list with all UCSD start-up deals. This list includes firms that used technology licensed from UCSD as the basis for initial formation and it contains names of start-ups, year of establishment, name of inventor/founder and financing information[9].

Combining the two set of records, I was able to match the licensees and group them into two types of firms: START-UP and ESTABLISHED.

The second source of my data set was the US Patent Office from which I collected data on the patents issued on the inventions (if any). I have constructed three variable: PRIOR ART – number of patents cited by the focal patent, PATENT CLASSES – number of classes that the patent is classified into, and CITATIONS – total number of citations received by the focal patent to date. These variables are used in my estimation to characterize the quality of the invention.

The final data set is an unbalanced panel consisting of 385 invention cases disclosed at UCSD between 1971-2003. Most of the disclosures are life science inventions, and the whole sample spans over 31 patent classes.

Table 1 reports some descriptive statistics regarding the inventions and the patents issued (if any) for the respective technologies. For inventions with multiple patents, the CITATION variable is the maximum number of citations for the individual patents (in order to avoid double counting of and self-citations).

Let me mention that many inventions are licensed very early after disclosure and they are protected by provisional patent applications[10]. Nonetheless, together with revenue, the variables in Table 1 are an important measure of the quality of inventions.

1.1.1 Licensing History: List of SECRECY agreements

The building block of my analysis is the list of agreements executed for each disclosed invention until the first license occurs (if any). In my analysis, this variable is constructed as the monthly number of secrecies for a given invention, for each period at risk until license or censoring event occurs[11].

The complete list of secrecies provides an important indication of the a priori knowledge of the potential licensee about the invention. The secrecies reveal information regarding the quality of the invention and the tacit knowledge imbedded in the invention. In addition, this list represents the Bayesian process of updating initial beliefs by potential licensees. In summary, secrecy agreements allow firms to learn more about the underlying value of the technology, mitigate the tacit knowledge problem, evaluate the quality of the match and decide whether to license the invention.

Practically, for a given invention, I would expect start-up firms to execute a smaller number of secrecies than established firms before licensing it (due to the superior information that inventor has about the use and value of technology). In other words, the number of secrecies previously executed on invention is more informative for established firms and consequently, it should affect more the hazard rate of license by established firms (as compared to hazard rate of start-up firms).

From Table1, the average number of SECRECIES per case until the first license occurs (if any) is 1.67, but there is a considerable variation among the inventions.

Table 2 relates the SECRECY variable to the event of license. Notice that more than half of the licenses are taken without any previous secrecy agreement. The average number of secrecies is 1.67 for licensed inventions and 2.22 for inventions with no license.

Another source of variation in the monthly number of secrecies comes from the identity of the licensee for the licensed inventions. As I mentioned before, the asymmetric information between the two types of firms is very important in the licensing process. Table 3 refers to this issue and shows the age of the invention and number of license agreements executed by START-UP and ESTABLISHED firms.

The table displays the data for the first 10 months of the inventions 'lives: notice that START-UP firms licensed 16 inventions in their first month of disclosure (10% of the total licenses by START-UP in my data set), while ESTABLISED firms only executed 4 licenses (2.6% of the total licenses by ESTABLISHED firms). Except for ages 2 and 3, the inventor-founder firms license more inventions than outside firms in the early life of the disclosures. This is consistent with my hypothesis that the start-up firms face less uncertainty about the value of technology and thus they could license the invention faster than established firms.

The underlying value of the invention is a key factor in the licensing decision. For example, if the invention is complex and very valuable, then a large number of secrecies might be needed the uncertainty about its value.

Can we infer something about the relationship between about the quality of technology and the type of licensee from the data? Ex post, an important measure of quality is the revenue generated by a given invention. This is a noisy proxy for quality, since revenue is affected by unobservable factors: management skills, potential market, competition, etc.

Table 4 shows the age of technology at license and the average revenue generated, by type of firm. In general, the inventions licensed by START-UP firms during the first months of disclosure generated more revenues than those inventions licensed by outside firms. One explanation is that START-UP firms have superior information about the underlying value of the invention even before disclosure. Thus, these firms are able to license the higher quality technology before the established firms, since outside firms generally need more time to reduce the higher uncertainty about the value of invention[12].

1.1.2 Theoretical Framework

On of the main assumptions of my basic theoretical model is that start-up firm are founded as a consequence of the utility-maximizing behavior of the inventor.

For simplicity, assume an inventor i disclosed and invention k which has a net present value of Π. In practice Π is difficult to estimate a priori and the actual return to licensee is the less or equal this value.

If the inventor licenses his own invention then she retains the entire amount Π; is the invention is licensed by an established firm the inventor receives $r\Pi$, where r is the royalty rate[13].

Let's denote $u_0(l, X)$ the utility function of the inventor without the start-up; the inventor's utility depends on leisure l and a vector of goods X.

Inventor's problem in this case is:

$$\max u_0(l, X) \quad \text{s.t. } 1)\ PX \le w + r\Pi \text{ and}$$
$$2)\ l + t^r \le 24,$$

where $P = (p_1, p_2, ..., p_n)$, $X = (x_1, x_2, ..., x_n)$ and t^r is the time spent on research activities at university (time constraint is expressed in hours/day).

Let $u_1(l, X)$ the utility function of inventor who forms a start-up firm. The problem of the inventor is now:

$\max u_1(l, X)$ subject to: 1) $PX \le w + \Pi$,

2) $l + t^r \le 24$.

The inventor chooses to license her own invention if the value of Π is high enough and the costs associated with starting a firm are not too high (the level of utility goes up by licensing own invention).

Suppose that an inventor discloses invention k at time t_o. At every moment $t > t_0$ invention k is at risk of being licensed by one of the two types of firms: START-UP or ESTABLISHED firm.

The invention has an underlying true value v_k, which is randomly distributed with probability density function $f(v)$ on the interval $[0, +\infty)$. Once the invention is disclosed and available for license, firms update their beliefs about v_k. For simplicity, we can assume that the initial belief about v_k for the established firms is zero. The start-up firms have superior information about the technology and thus their initial belief about the value is closer to the true value.

In addition, let me denote by $h^{t_1}{}_k$ the complete history of all SECRECY agreements executed for invention k until t1: $h^{t_1}{}_k = \{$ SECR$_1$, SECR$_2$,….,SECR$_m\}$.

The history of secrecies (more precisely, the whole licensing history) is observable by all potential licensees, and includes names of potential licensee, type of firm and date of agreement.

Only one firm (if any) can license a given technology for every period that the invention is available for license.

1.1.3 Firm's Objectives

In my model, firm i's objective with respect to invention k is to maximize the expected value of the match between the firm and invention the invention: max $M_k{}^i(f_i, k)$.

In order to meet its objective, the firm can execute a SECRECY agreement to learn more about the true value of the invention and update its initial beliefs.

Having executed a SECRECY agreement, firm i's conditional expected value of the match with invention k is:

$$M_k{}^i = \int_0^\infty g(v, X, h^{t_1}{}_k) f(v) dv, \qquad (1)$$

where g is an increasing function in v and X is a vector of variables characterizing the quality of invention and match (e.g. type of firm, size, management skills etc).

Notice that the history path of secrecies has an informative value for the firm. Firm updates its initial beliefs about v not only by executing its own SECRECY agreement, but also by using the information contained in $h^{t_1}{}_k$.

The optimal policy of a firm i is to licenses the invention if the expected value of match with that invention exceeds a lower bound $\underline{\mu}$, or:

$$\int_0^\infty g(v, X, h^{t_1}{}_k) f(v) dv \ge \underline{\mu}.$$

The probability that an invention k disclosed at time t0 survives without a license, given no events occurred through time t is:

S(t| X, $h^{t_1}{}_k$)=1-Prob($M^i{}_k < \underline{\mu}$),

for all firms i which tried to license the invention up to t.

To summarize, the heterogeneity is introduced through two important channels: distribution of the true value of invention, and asymmetry of information about the use of the technology.

This model can also formalize the strategic interaction of the licensing process, since the decision to license is conditional on previous firm not licensing the invention.

The effect of asymmetric information on the probability of license of a given invention can be described by the effect of secrecy agreements on the hazard function (the event is the invention being licensed). Denote by $\left|h^{t_1}{}_k\right|$ =card ($h^{t_1}{}_k$), i.e. the total number of elements in the history vector.

Thus, an important question arises: what is the expected sign of the term $\frac{\partial H_k}{\partial |h^{t_1}{}_k|}$?

where H_k is the hazard rate for the invention k.

Inventor-founder firms (START-UP) have superior information about the use of technology and underlying value of invention. Thus, we could expect that, effect of $\left|h^{t_1}{}_k\right|$ on likelihood of license is smaller for START-UP firms than for ESTABLISHED ones.

The ESTABLISHED firms, for the same underlying value of the invention, use more the SECRECY agreement to make up for the asymmetry of information.

The total number of secrecies for a given invention is correlated with the underlying value of the invention. For example, a valuable invention could display more secrecies relative to a less valuable invention, since the many potential licensee are interested in licensing that invention.

If the invention k is licensed, then the following has to be true at the limit (lower bound limit for the expected value of the match):

$$\int_0^{\infty} g(v, X, h^{t_1}{}_k) f(v) dv = \underline{\mu} .$$

The above equation and the first order conditions of inventor's utility maximization problem can be used to obtain a relationship between the number of secrecies, value of invention, and other covariates.

1.1.4. Estimation Methodology and Results

In order to estimate the survival functions and effect of invention's characteristics on the probability of license I use a competing risks model similar to Thursby (2003). Having been disclosed, a given invention is at risk of being licensed by either a START-UP firm or an ESTABLISHED firm.

If X_i is the i^{th} latent lifetime of the invention ($i = 1,2$), then from the data we observe the type of the firm and the random variable $T = \min(X_1, X_2)$.

The probability of an invention to be licensed by a START-UP (ESTABLISHED) firm conditional that it was not license through period t-1 is:

Prob$(T_{su} = t \mid \Omega, T > t-1) = 1 - \exp(-\theta_{su} \exp(\Lambda_{su,t} + \beta'_{su} x))$, and (1)

Prob$(T_{estb} = t \mid \Omega, T > t-1) = 1 - \exp(-\theta_{estb} \exp(\Lambda_{estb,t} + \beta'_{estb} x))$, (2)

where Ω is a set of covariates characterizing the invention and the licensing history.

The joint survivor function can be written as:

$$S(t_{su}, t_{estb} \mid \Omega) = \exp(-\theta_{su} \sum_1^{t_{su}} \exp(\Lambda_{su,t_{su}} + \beta'_{su} x) - \theta_{estb} \sum_1^{t_{estb}} \exp(\Lambda_{estb,t_{estb}} + \beta' x)), \quad (3)$$

where Λ is the baseline hazard function for each type of firm.

Data is organized as follows: every row in the data corresponds to every month that a given invention has been under risk of being licensed (starting from disclosure data). Figure 1 presents the Kaplan-Meier estimate of the monthly survival function and the cumulative baseline hazard function (Fig. 2). Duration time is discrete and measured in months from disclosure.

More than 50% of the total inventions are licensed in the first 2 years after disclosure and the maximum age at which an invention was licensed is 160 months. For start-ups (established), the earliest exit is at age of 1 month (1 month) and the last exit at age of 146 months (160 months).

Table 6 reports the estimated coefficients for the regression of revenue on some of the invention's characteristics and a dummy variable for start-up firms (=1 if invention was licensed by a start-up firm). In order to ensure that the results and specification of this regression are accurate, I have excluded a couple of outliers before running the regression. As expected, the revenue increases with time from disclosure and number of patents issued on a given invention; but the interesting results are provided by the SECRECY and start-up dummy variable. First, there is a U-shaped relationship between the revenue and total number of secrecies. Secrecies function as a signaling device and help the potential licensee learn about the quality of inventions (they affect the revenue though expectations and updating mechanism).

Second, the coefficient for start-up dummy variable is significant and positive. This result can be driven by the fact that start-up firms license higher quality inventions.

To summarize, these two results (combined with Table 4) bring stronger support for my hypothesis that start-up firms license higher quality inventions faster than outside firms. This is a result is driven by the asymmetry of information about the value of the technology between the two types of firms.

Tables 7 and 8 report the results for the independent competing risks model: START-UP and ETABLISHED firms compete to license a given invention. The baseline hazard function was characterized by exponential, Weibull and Cox Proportional Hazard specifications and the tables report the estimated coefficients for the covariates. Figure 2 presents a graphical representation of the likelihood of license functions for both types of firms.

The key result from these two tables is that SECRECY variable have a positive effect on the probability of license, and this effect is bigger for ESTABLISHED firms than for START-UP. Under a Weibull specification, if the SECRECY increases by 1 unit then the monthly hazard of being licensed for a given invention goes up with 4.8% for START-UP firms and by 7.3% for ESTABLISHED firms.

Using a Cox Proportional hazard specification the monthly hazard increases by 7.7% for START-UP and 8.6% for ESTABLISHED. Let me also mention that for tables 7 and 8, I have included controls for technological field effects by using patent class dummies for each of the patent classes included in the sample (eg. c_i is a dummy variable taking on the value of 1 if the patent class is i, i=1,31).

These estimation results provide evidence in support of my theoretical assumption that asymmetric information (which can be described by the licensing history) has a different impact on the probability of license by the two types of firms. An extra SECRECY executed on the invention has more informative value for established firms; the likelihood of licensing by established firms increases in general by 2.5-4% more than for start-up firm. Again, from the point of view of tacit knowledge problem, an extra secrecy executed on the invention reduces the uncertainty about the invention more for an established firm relative to the start-up firm; as a result an extra secrecy has a bigger effect on the likelihood of license for established firms relative to start-up firms.

With respect to the SECRECY variable, I have tried to include an additional variable, SECRECY SQUARED, in the specifications mentioned in tables 7 and 8. For start-ups, the coefficient for SECRECY SQUARED is negative but not significantly different from zero; for established firms, the coefficient is positive but not significantly different from zero. Thus, this variable was dropped and not reported in my results.

Other important results are provided by the estimated coefficients for the measures of quality. With respect to the PATENT CLASS variable (number of classes that the patent fits into, according to US Patent Office), the theory suggests that the patent is more valuable the broader is its scope, i.e. the more classes can be classified into.

The mean of PATENT CLASS for start-ups is 3.77 and for established firms 2.96; this is a first indication that on average, start-ups license more valuable inventions.

Comparing the results in tables 7 and 8, the exponential specification delivers a bigger coefficient of patent class for start-up firm. This is consistent to my model that inventor-founder firms license the better quality inventions.

The PRIOR ART coefficient is positive for start-ups and negative for established firms. Since a decrease in PRIOR ART is associated to a more novel and hence risky knowledge, the coefficients indicate that established firm are more likely to license more novel technologies. This conclusion is in contrast to the findings in Lowe (2002), in which the inventor-founder firm are more likely to license novel technologies due to high costs involved in contracting tacit knowledge.

CITATION variable does not have any significant impact on the hazard function. I discuss the shortcomings of this variable and ways to improve the estimation precision in the last section of the paper, Conclusions and Directions of Future Research.

It is worth mentioning the sign of the dummy patent, which is negative. One possible explanation for the negative sign is that once the patent is issued then the established firms can use the details provided in the patent to imitate the technology and advance their own research without the need of the inventor. Thus the start-up firm has less incentive to license an invention for which a patent was issued because the value of such invention was reduced.

On the other hand, the dummy variable patent has a different effect for the established firms: once issued, the patent reduces the asymmetric information between the two types of firms. Established firm can learn a lot about the invention through the patent and this has a positive effect on the hazard of license. This effect turns negative after 12 months because if the invention was not licensed till then it might be of a poorer quality.

The independent competing risks model assumes that there is no correlation between the unobservable factors affecting each destination-specific hazard. In practice, this assumption might not be entirely realistic. For example, a start-up firm might license an invention because no outside firm licensed it for a period of time.

If one ignores the unobservable factors, the estimation procedure delivers biased results. This is due to a selection process: since large θ's (unobservable factors) imply large hazard and high probability to exit, other things being equal, the group of surviving inventions is increasingly made up of inventions with relatively low θ's.

Following Thursby(2003), the correlation in unobservable factors is described by two pairs of thetas: $(\theta_{su,i}, \theta_{estb,i})$, $i = 1,2$ which occur with probability p and (1-p) in the entire sample. The baseline hazard function is now described as a second order polynomial:

$$\Lambda_{i,t} = \delta_{i1} t + \delta_{i2} t^2 ,$$

$i = 1,2$ for START-UP and ESTABLISHED firms.

Denote by $\phi_{su}(k), \phi_{estb}(k)$ and $\phi_c(k)$ the unconditional probabilities of an invention to be licensed by a start-up firm by the beginning of period k, the unconditional probability of an invention to be licensed by an established firm by the beginning of k, and the unconditional probability that an invention is licensed by neither types of firms by the beginning of period k. Then, we can write:

$$\phi_{su}(k) = S(k-1, k-1 \mid \Theta) - S(k, k-1 \mid \Theta) - 0.5[S(k-1, k-1 \mid \Theta) + S(k, k \mid \Theta) - S(k-1, k \mid \Theta) - S(k, k-1 \mid \Theta)]$$

$$\phi_{estb}(k) = S(k-1, k-1 \mid \Theta) - S(k-1, k \mid \Theta) - 0.5[S(k-1, k-1 \mid \Theta) + S(k, k \mid \Theta) - S(k-1, k \mid \Theta) - S(k, k-1 \mid \Theta)]$$

$$\phi_c(k) = S(k-1, k-1 \mid \Theta),$$

where the last term in the ϕ_{su}, ϕ_{estb} is an adjustment due to discrete form of the data.

The log-likelihood function is (there are 3 possible destinations: licensed by start-up, established or censored):

$$\log L = \sum_{1}^{N} \sum_{k=1}^{K_n} d_{su,k}{}^n \log \wp_{su,k}{}^n + d_{estb,k}{}^n \log \wp_{estb,k}{}^n + (1 - d_{su,k}{}^n)(1 - d_{estb,k}{}^n) \log \wp_{c,k}{}^n , \qquad (4)$$

where $\wp_{i,k} = \sum_{j=1}^{2} p_j P_i(k \mid \Theta_j)$, $\Theta_j = \{\theta_{su,j}, \theta_{estb,j}\}$.

In order to estimate the parameters of interest, an ML procedure was used for the log-likelihood function in (4). The results of the MLE are reported in table 9. Notice that SECRECY maintains the positive coefficient for both types of firms, as in the independent risks case.

The variable PRIOR ART has positive sign for start-ups and negative for established firms. These coefficients suggest, as in the case of independent risks approach, that start-up firms are more likely to license inventions with more prior art cited, in other words less uncertain and risky technologies. On the other hand, established firms seem to be more likely to license more novel technologies.

A possible explanation might be that start-up firms are usually small in size (less than 10-15 employees), have less experienced management team and more constrained financially. Thus, these firms generally might license less uncertain technologies, and which require less investment to develop.

PATENT CLASS variable has a positive coefficient for both types of firms, slightly higher for established firms. The probability of the first pair of theta coefficients is approximately p = .26 and the unobservable factors are positive[14].

The dependant competing risks estimation generally strengthens the conclusions from independent risks case. The secrecy variable, which contains the a priori beliefs about the value and the updating mechanism, has a different effect on the likelihood of license for the two types of firms. The measures of quality indicate important differences in the characteristics of the technology being licensed by start-up and established firms.

As a general conclusion, the analysis of licensing process based on two specific destinations (inventions can be licensed by start-up or established firms) provides us with a more complete and detailed description of the technology diffusion mechanism.

The asymmetry of information between start-ups and established firms play an important role in determining the quality of technology licensed. But other characteristics of the firms (size, management skills, financial resources) might also affect the licensing process.

1.1.5. Conclusions and Directions for Future Research

In this paper, using a unique data set from the UC San Diego campus, I employ a new methodology to analyze the diffusion of technology through START-UP and ESTABLISHED firms.

START-UP formation is modeled as a result of utility maximizing behavior of inventor. Due to asymmetric information, inventors face lower uncertainty about the underlying value of their inventions than outside firms. Once disclosed, the invention is at risk of being licensed by either a start-up or an established firm.

I report two main results. First, I show that the number of SECRECY agreements (which reflect the asymmetric information and Bayesian process of updating initial beliefs about the value of invention), have a positive effect on the likelihood of license by firms. In particular, there is evidence that this effect is bigger for established firms. This finding is very important in understanding the dynamics of the licensing process: secrecies have a signaling and informative value to the firms and they affect the hazard of license. The data suggests that start-up firms license technology faster than established firms, in particular at early stages of invention’s lives.

Second, I bring evidence that there is a sorting effect with respect to the quality of inventions: START-UP firms are more likely to license higher quality inventions than ESTABLISHED firms. This empirical result supports the assumption of the theoretical model: if the expected value of the invention is high enough, the inventors respond optimally by licensing their own inventions through start-up firms and increase their utility level.

There are areas of further improvement and research in my paper. Using that secrecy agreements have a signaling and informative value to potential licensee, I would like to develop a full theoretical model based on the framework presented in Section 3[15]. This model will be based on the utility maximization problem of the inventor, firm's objectives (maximize the expected value of the match with the invention, or expected profits) and incentive mechanism and constraints due to university regulations. Variable SECRECY could be included as an externality to the licensing process. Formalizing the Bayesian process of updating beliefs about the underlying value of the invention is going to be the central feature of the theoretical model.

The data available allows me to include in the analysis other characteristics of the licensing process. One example is the type of the license used: exclusive or non-exclusive. Do start-up firm usually license technology through exclusive or non-exclusive license? The type of license is determined by many factors: potential market for technology, state of technology (embryonic, or in final stages of research), field of use. Exclusive licenses usually apply to technologies in very early stages of development and which require a big investment commitment in order to fully develop them; some technologies are best to be licensed through non-exclusive licenses.

With regard to the empirical analysis, I plan to improve the estimation results for the CITATION variable; this would provide me with an additional measure of quality for the technology licensed by the two types of firms[16].

Using the preliminary results of Table 6, I will analyze in detail the non-linear relationship between the revenue (measure of quality) and the secrecy variable. A simple graphical representation of the two variables suggests the existence of three distinct regions: the first region is associated with small number of secrecies and high revenues, the second one is characterized by medium number of secrecies and medium revenue and the third region with high number of secrecies and high revenues.

Finally, I would like to address the issue of policy-making implications with regard to the efficiency of the technology diffusion process. In order to do that, a comprehensive approach should include objectives of inventors and firms, university strategic goals and the public benefits. From societal point of view, a welfare analysis of the technology diffusion process could provide valuable lessons in how to improve the process of innovation and successful commercialization at universities. State and national incentives and policies must be designed optimally in order to maximize the total welfare ijn society from these Activities.

Start-up takeovers and mergers represent another channel for technology diffusion and could be included in the cost-benefit analysis. That could be an important avenue for research in the field of management of innovation and technology.

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Notes

Note 1. I am indebted to the Alexa Faulkenstein at TechnologyTransfer and Intellectual Property Services, UCSD for providing me with the data on start-ups and inventions and graciously answering my subsequent queries.

Note 2. Special thanks to Macias Brian at **UCSD Connect** with whom I had numerous interviews; he kindly provided me with a history of biotech sector in San Diego and gave guidance to various sources of information for my research.

Note 3. The 1980 Federal Bayh-Dole Act, which gave the universities the right to commercialize intellectual property developed with federal funds.

Note 4. The inventor might put too little effort in the absence of this incentive scheme.

Note 5. High costs occur as a result technological uncertainty and tacit knowledge

Note 6. Numerous interviews with Macias Brian at UCSD Connect, and A. Faulkenstein at TechTips, UCSD have suggested that inventors form a priori beliefs about the value of their inventions and then found START-UPs to retain most of rents resulting from licensing their own inventions.

Note 7. Technology Transfer and Intellectual Property Services, UCSD.

Note 8. The first obligation of a researcher is to disclose the invention so that property rights can be assigned.

Note 9. This information contains: initial capital raised, date and amount of IPO, UC equity stake in the firm (if any) and the status of the firm (active, merged, public or bankrupt).

Note 10. A patent number is issued between 1-5 years after application date; in some cases the patent application is abandoned by the licensee if technology is not as desired from quality point of view, or other reasons.

Note 11. Two risks can claim the 'life' of an invention: license taken by a start-up or established firm.

Note 12.For a given invention, inventor-founder firm could be a better match than an established firm. Superior information about the technology translates into higher rents extracted from the invention by start-ups.

Note 13.Royalty rate is 35% at UC now but the inventor receives, in expectation, less than since an established firm might realize the full potential of invention due poor match or other reasons. The possibility of a poor match with an outside firm provides an extra incentive for the inventor to license his own invention through a START-UP.

Note 14. Unobservable factors capture the effect of omitted variables, error in measurement of regressors or quality characteristics of the inventions. The inventions are now composed of 2 subgroups: one group represents 26% of the sample and the second group 74%; each subgroup is homogenous with respect to unobservable characteristics.

Note 15. I have already started to work on a detailed theoretical model in which firms enter secrecy agreements in order to learn about the true value of invention.

Note 16. Some patents were issued very recently in my sample and they do not have too many citations yet. For newer patents, I will predict the number of citations by choosing a random sample of patents from similar technological fields and were issued much earlier.

Table 1. Descriptive Statistics

	Mean	Std. Dev	50%	75%	90%
SECRECY	1.67	2.47	1	2	5
PRIOR ART	4.51	8.52	0	6	13
PATENT CLASS	3.37	20.47	2	6	10
CITATIONS	6.71	16.37	0	6	19

Table 2. SECRECIES and LICENSE EVENT

# Secrecies	License Event =1	License Event = 0	Total
0	26	126	152
1	23	85	108
2	5	21	26
3	7	15	22
4	2	19	21
5	3	9	12
6	1	10	11
7	4	2	6
8	1	6	7
9	1	6	7
10	1	3	4
11	3	1	4
12	0	2	2
14	0	2	2
17	0	1	1
TOTAL	77	308	385

Table 3. Age of Invention and Number of License Agreements by Type of Firm

Age of Invention (months)	# Licenses: START-UPs	# Licenses: ESTABLISHED
1	16	4
2	1	2
3	2	5
4	8	4
5	8	7
6	12	10
7	6	3
8	7	2
9	6	3
10	2	5

Table 4. Age of Invention at license, Average Revenue and Type of Licensee

Age of Invention (# months)	Start-up: Average Revenue	Established: Average Revenue
1	$30,617	$10,805
2	$166	$907
3	$5,297	$11,038
4	$17,955	$1,025
5	$5,884	$4,485
6	$17,880	$3,389
7	$14,903	$6,438
8	$27,459	$9,488
9	$16,577	$8,541
10	$4,525	$8,842

Description for Table 2-3 above

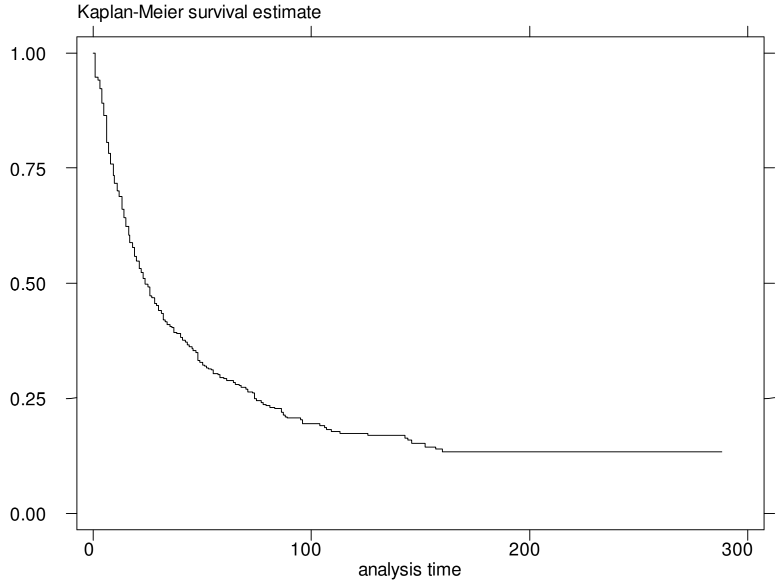

Fig. 1. Table 5. Kaplan-Meier Survival Function Estimate and Cumulative Hazard
Description for the above Figure

Table 6. Quality of Inventions: Revenue and Other Characteristics

	Total Revenues
Invention Age	93.29852 (180.5335)
Invention Age Squared	-2.068497 (2.92678)
# Patents	75968.08* (10490.88)
Secrecy	-32847.24* (9020.263)
Secrecy Squared	4876.156* (720.7617)
Citations	2328.204* (984.1503)
Dummy for start-up	55351.32* (27868.63)

Note: Standard errors reported in parenthesis and an asterisk denotes significance at 5% level.

Table 7. Results of the Independent Competing Risks Model for START-UP firms

	COX PH	Weibull	Exponential
secr0 x t1	.902757 * (.3573833)	1.139641* (.2636423)	.9513966* (.2313041)
secr0 x t2	-.1262215 (.3722376)	-.2633518 (.3624215)	-.1921369 (.3590248)
SECR x t1	.0620815 (.0852909)	.0942035 (.0632572)	.0790664 (.0640381)
SECR X t2	.051525 (.0419644)	.0327315 (.0483042)	.0450903 (.0467619)
d_pat	1.346953* (.2475179)	1.37294* (.2851167)	1.339896* (.2842306)
pat_class	-.0407169* (.0193515)	-.0412465 (.0293018)	-.0396654 (.0292243)
prior_art	.0138088* (.003482)	.0136059* (.0061348)	.0129237* (.0061266)
d_nexcl	-.2868585 (.4125355)	-.2723809 (.4029099)	-.267986 (.4023712)
citations	.0041681 (.0018526)	.0042531 (.003706)	.0040855 (.0037342)
T1	-1.973366* (.7831674)	-2.259673* (.7593823)	-2.140032* (.7540136)
T2	-2.813008* (.6621927)	-3.152763* (.63795)	-3.035529* (.6318045)
T3	-1.335298* (.3563865)	-1.472748* (.3534884)	-1.370206* (.3460116)
T4	-1.447966* (.3447516)	-1.468144* (.3355439)	-1.398474* (.3315137)
T5	-.7640075* (.2775301)	-.781964* (.2875658)	-.7402655* (.2756823)
Const.	-	-4.835044* (.445575)	-4.339178* (.2878191)

Key: An asterisk denotes significance at 0.05 level.

Table 8. Results of the Independent Risks Model for ESTABLISHED firms

	COX PH	Weibull	Exponential
secr0 x t1	.8165196* (.4091403)	.5956504* (.2865324)	.4241793** (.2510115)
secr0 x t2	-.0402001 (.312769)	-.0009135 (.3040543)	.0710453 (.2979808)
SECR x t1	.1718506* (.0869459)	.114808** (.0693263)	.1008457 (.0700011)
SECR X t2	**.0906772**** (.0483708)	**.0956123*** (.0439908)	**.1058762*** (.0426157)
d_pat	1.338653* (.4284518)	1.428455* (.4248553)	1.390635* (.4220478)
pat_class	-.0509691 (.0413735)	-.0467192 (.042712)	-.0455481 (.0425477)
prior_art	-.0307599 (.0258316)	-.0305319 (.0260034)	-.0306824 (.0258863)
d_nexcl	1.641281* (.1933317)	1.778304* (.2100359)	1.748692* (.2078227)
citations	-.0149261 (.0104668)	-.0145765 (.0140887)	-.0148771 (.0141888)
T1	-.7790611* (.4293211)	-1.115338* (.4524918)	-.9909827 (.4400722)
T2	-1.620983* (.3364659)	-1.986098* (.377451)	-1.864384 (.362581)
T3	.657617* (.39629)	-1.84017* (.3861515)	-1.732344 (.375502)
T4	-1.713878* (.3782789)	-1.899864* (.377646)	-1.814362 (.369967)
T5	-.849265* (.2760326)	-.9237937* (.2880284)	-.8683797 (.2838148)
Const.	-	-4.714458* (.4719465)	-4.266735 * (.2959211)

Table 9. Cox PH regressions - Robustness check with class dummies

	Start-up Model 1	Start-up Model 2	Established Model 1	Established Model 2
Secre0	4692208* (.2329587)	.4853457* (.2345277)	.5106347* (.2293622)	4883176* (.2211664)
SECR	.0551388 (.0451374)	.0553776 (.0451805)	.0995088* (.0397453)	.0990208* (.0387737)
d_pat	1.215134* (.1649821)	1.276419* (.1753818)	0184413 (.2092031)	2..393593* (.2929565)
Chemical	**No**	**Yes**	**No**	**Yes**
Comp&Comm	**No**	**Yes**	**No**	**Yes**
Drugs&Medical	**No**	**Yes**	**No**	**yes**

Key: * p < 0.05 (two-tailed); Yes : control for technological field, No: no controls for technological fields.

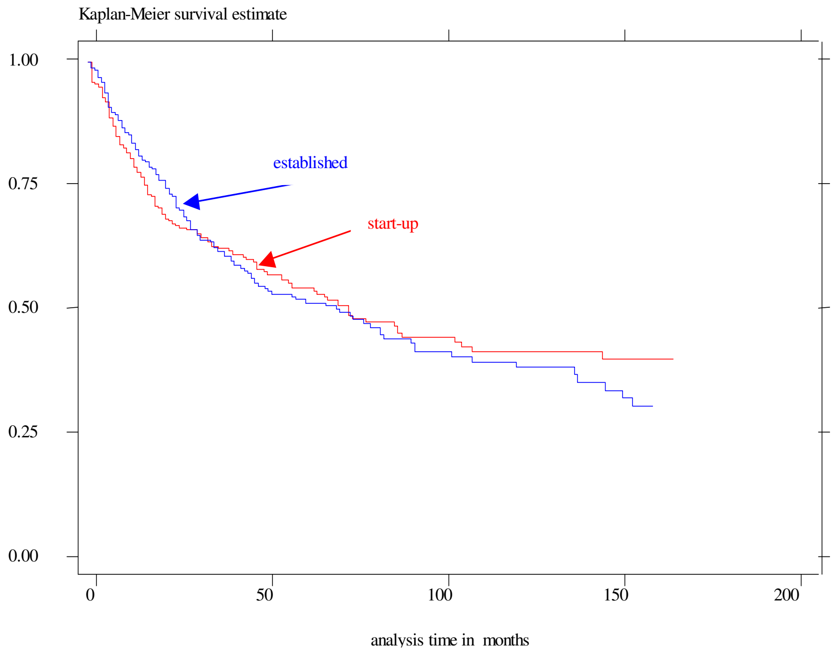

Figure 2. Kaplan-Meier Survival function for Start-ups and Established Firms
Description for the above figure