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Robert A. Lowe, Arvids A. Ziedonis,

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Overoptimism and the Performance of Entrepreneurial Firms

Robert A. Lowe
Social and Decision Sciences, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, roblowe@andrew.cmu.edu

Arvids A. Ziedonis
Stephen M. Ross School of Business, University of Michigan, 701 Tappan Street, Ann Arbor, Michigan 48109, azied@umich.edu

Recent theoretical and empirical research on cognitive bias in decision making suggests that overoptimism critically influences entrepreneurs' decisions to establish and sustain new ventures. We investigate whether such cognitive bias influences entrepreneurial venture performance using data on commercialization efforts for university inventions. In contrast to prior studies, our results suggest that entrepreneurial overoptimism does not appear to be the determining factor in the decision to found a firm. We do find that entrepreneurs continue unsuccessful development efforts for longer periods of time than do established firms, which is consistent with entrepreneurial overoptimism in the development of technologies with uncertain market prospects. This latter finding is also consistent with rationality-based models of decision-making behavior, however. We find that the economic returns associated with many of the technologies in our sample are realized after the start-up has been acquired by an established firm, suggesting that start-ups may serve as a transitional organizational form in the market for technology commercialization.

Key words: entrepreneurship; university technology transfer; cognitive bias
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1. Introduction

Entrepreneurial firms have long played a significant role in the commercialization of university inventions, often pursuing product development after existing firms fail. For example, in 1945 the Massachusetts Institute of Technology (MIT) licensed rights to its Van deGraff patent to High Voltage Inc., a start-up formed specifically to bring the MIT technology to market. High Voltage obtained its license only after the General Electric Company had earlier licensed this patent and failed to commercialize the technology (Etzkowitz 2002). More recently, Calimetrics, a start-up founded by a University of California inventor, was founded to commercialize an optical storage technology previously licensed by Uniphase (Lowe 2001). In the biotechnology industry, Chiron and Genentech are two notable firms established to commercialize inventions originating in the university lab.

Recognizing the importance of entrepreneurial firms in commercializing these early-stage technologies, universities have been increasingly willing to invest in newly established ventures. In a 2000 survey, Feldman et al. (2002) found that 40% of research universities surveyed held equity investments in new firms licensing their technology. These equity positions have sometimes been profitable for university investors. For example, the University of California received $1.9 million from its equity in software firm Inktomi (UC Technology Transfer Annual Report 2000 (2001)) and Carnegie Mellon University held considerable equity in and a board seat at search engine Lycos, both of which issued lucrative initial public offerings during the late 1990s.

Despite these entrepreneurial success stories and the increasing enthusiasm for new firms as vehicles for bringing university technologies to market, commercializing new technologies through start-ups instead of more established firms involves important trade-offs. Start-ups often lack access to complementary assets necessary to successfully bring a product to market, such as market knowledge, contacts with customers, or manufacturing capabilities (Teece 1986). Because these firms are typically founded for the sole pursuit of commercializing a single licensed technology, they may be unable to diversify risks in new technology development across multiple technologies as can established firms, contributing to high rates of failure. Start-ups also may be unable to reap the economies of scale in research and technology development enjoyed by larger firms, postponing or even preventing new product introduction (Nelson 1959). Indeed, Shane (2002) found that in those technology fields where patent effectiveness was weak, inventor-founded licensees from MIT were more likely to terminate a license and less likely to introduce a new product based on the licensed technology than an established licensee, leading him to conclude that licensing to an inventor-founded start-up is less desirable than licensing to an existing firm.

University inventions typically represent early-stage or pre-prototype technologies with highly uncertain prospects. In a survey of 52 university technology transfer offices, Jensen and Thursby (2001) found that over 75% of inventions disclosed to the technology transfer office represented only a "proof of concept" or a lab-scale prototype. Faced with such obstacles and risks, why would a would-be entrepreneur establish a start-up to pursue commercialization of a university technology? For the faculty inventor, one reason could be that transaction costs in transferring technology to an outside firm (such as adverse selection, moral hazard, or thin markets) may prevent the market for technology from operating smoothly (Arora 1995, 1996; Shane 2002). Much of the knowledge necessary to understand the technology may be tacit, making it difficult, if not impossible, for the inventor to transfer this knowledge to the licensee, despite contracts that may be designed to support such transfer (Arora 1995, 1996). Because tacit knowledge transfer would not be necessary for an inventor-founded start-up, the inventor may be able to realize greater monetary returns if she commercializes the invention herself (Shane 2002, Lowe 2001).

Overconfidence and other forms of cognitive bias also may be behind entrepreneurial initiative in commercializing university inventions. Since the influential studies by Kahneman and Tversky (1979) of human decision making, elements of cognitive bias have been identified in a wide variety of decision-making situations. For example, self-serving perceptions of fairness have been shown to cause impasses in labor-management negotiations (Babcock et al. 1996) and differences in defendant and plaintiff assessments of just monetary awards in property damage situations (Babcock and Lowenstein 1997). Security analysts have been found to make biased predictions of stock market performance (De Bondt and Thaler 1990), as have individual stock market investors (Odean 1998).

Managers and entrepreneurs also may not be immune to cognitive bias and its negative effects. Hubris (Roll 1986) and overconfidence (Hayward and Hambrick 1997, Malmendier and Tate 2004) by executives are offered as explanations of overpayment by acquiring firms for takeover targets. Kahneman and Lovallo (1993, p. 27) cite the substantial mismatch between entrepreneurs' predictions of their chances of success and actual survival data of start-up firms as a "compelling example" of entrepreneurial overconfidence. Similarly, Camerer and Lovallo (1999) observe that overoptimism in market entry may be an important factor contributing to failure among new firms.

In this paper, we consider whether the "second-best" outcome of licensing to start-up firms (Shane 2002) may be due to entrepreneurial overoptimism. To do so, we compare the performance of start-ups with that of established firms in developing and commercializing university inventions. Our analysis considers three aspects of performance: (1) likelihood of achieving commercial sales, (2) likelihood of terminating a development effort, and (3) university licensing revenues generated by a developed invention. Despite the prevalence of overconfidence in a wide variety of decision-making situations, there has been little research on overoptimism in university technology commercialization.

Our results suggest that, on average, entrepreneurs commercializing university technology do not appear to be overoptimistic in their decision to start a firm: Start-ups exhibit statistically equivalent performance rates to established firms in commercializing university inventions. We also find that licenses to these start-ups generate licensing revenues at least as high as the revenues for licenses to established firms. These results hold even once we control for technology field, location, and time effects. More in line with an overoptimism bias, our second main finding is that start-ups continue unsuccessful development efforts for longer periods of time than do established firms. The rate of project termination is significantly lower for start-ups than for established firms, and these results persist even after controlling for the project's scientific field of origin. While our second main finding is consistent with overoptimism bias, it is also consistent with rationality. Further analysis calls into question whether entrepreneurs may be overoptimistic in continuing to develop products with possibly limited chances for future success.

In contrast to earlier studies (e.g., Shane 2002), we find little evidence that licensing to start-ups represents a "second-best" solution. As discussed in §5, part of this divergent finding may be driven by the intermediary role played by start-ups in the process of commercializing these early stage technologies. While the university inventions were initially licensed to start-ups, the economic returns associated with many of the technologies in our sample were realized after the start-up had been acquired by an established firm. We discuss this finding, alternative explanations, and implications for future research in §5.

In the next section, we briefly review recent studies of university technology licensing to entrepreneurial firms and the literature on managerial cognitive bias, and develop our hypotheses. Section 3 describes the data and our methodology, and §4 presents the results of our empirical analysis. We discuss the implications of our findings and conclude the paper in §5.

2. Hypothesis Development

In ambiguous environments, individuals are more likely to be overoptimistic (Camerer and Lovallo 1999). For example, in a study of the scientific and commercial development of three technologies championed by university researchers (the artificial heart, cochlear implants, and the FK 506 immunosuppressive drug), Garud and Ahlstrom (1997) found that developers of these technologies overestimated patient benefits and underestimated the time and cost necessary to develop the technology and gain FDA approval. Researchers considered each of these technologies to be unique, leading them to employ limited evaluation criteria compared to outside reviewers who compared the new technology to similar medical technologies developed earlier. The reviewers also considered a broader range of factors that could delay commercialization but were largely ignored by the researchers, such as related technological issues, production problems, and ethical and quality of life issues. Similarly, Simon and Houghton (2003) found that managers introducing "pioneering" products (i.e., products entering new and uncertain markets) exhibited significantly greater overconfidence than managers introducing products embodying incremental innovations.

Overconfidence has also been demonstrated in experiments on decision making regarding market entry. Camerer and Lovallo (1999) found evidence of excess entry in experiments where participants were ranked according to skill compared to entry in control experiments where participants were given a randomly assigned skill level. Moreover, even though participants estimated accurately the number of entrants and realized that the expected value of entering was negative, excess entry still occurred, consistent with overestimation by individuals on their own prospects for success (de Meza and Southey 1996, Arabsheibani et al. 2000).

Kahneman and Lovallo (1993) conclude that such confidence can result from approaching problems or new initiatives from a self-centered and limited perspective, leading to "bold forecasting." They argue that managers frequently adopt an "inside view," constructing detailed plans or scenarios to achieve the desired outcome. Treating the problem in isolation and viewing risks as challenges to be overcome through knowledge and experience can lead to overoptimism. In contrast, an "outside view" taken by the third-party reviewers does not focus on unique project plans and details to assess a project's prospects. This view ignores detailed projections and instead compares a particular project to a similar class of completed projects to estimate the probability of success, likely producing a more realistic projection of the eventual outcome.[1]

Other studies suggest that this cognitive bias may be more pronounced among entrepreneurs than managers of established firms. For example, Bercovitz et al. (1997) suggest that entrepreneurial bias and managerial bias operate in distinctive ways. Whereas entrepreneurs are concerned with early-stage technologies and their prospects along emerging technological trajectories, managers at established firms compare new innovations to their existing products and technologies. Overconfidence by entrepreneurs can therefore lead to greater difficulty than expected in developing an innovation along the new technological trajectory. In contrast, overoptimism by managers at existing firms can lead to overestimating the ability of existing resources to develop incremental innovations that can compete with radical innovations.

Busenitz and Barney (1997) also explore differences in cognitive bias between entrepreneurs and managers in existing firms. They argue that managers and entrepreneurs employ different decision-making processes to deal with risk and uncertainty. Existing firms are more likely to have established decision-making "routines," which reduce complexity facing managers (Nelson and Winter 1982). Moreover, managers at existing firms often have greater access to historical trends and data than do entrepreneurs on which to base their analyses. In contrast, start-up firms typically have not developed detailed policies governing decision making, causing entrepreneurs to be more likely to rely on simplifying biases and heuristics. Entrepreneurs developing technologies in emerging technological trajectories also must often act quickly with limited information on technical feasibility and market conditions to convince financiers, employees, and other stakeholders of the start-up opportunity's prospects. This further encourages entrepreneurs to rely on simplifying heuristics to speed decision making. Busenitz and Barney (1997) therefore hypothesize that entrepreneurs will express greater overconfidence than managers. To empirically test this hypothesis, they surveyed 573 new firm founders and existing firm managers and found

[1] Kahneman and Lovallo (1993) point out additional factors that may generate overoptimism at an organizational level. For example, forecasts and plans may be generated by those with a vested interest in the project's acceptance. When projects compete with others for acceptance, there may be incentives to overstate calculations and estimates. Projects with the most overoptimistic estimates may be the most likely to be accepted. Pessimistic views may be suppressed during the acceptance process, leading to a lack of critical evaluation.

that entrepreneurs demonstrated significantly greater overconfidence in their survey responses than did managers of existing firms.

Comparing perceptions of financial risk between entrepreneurs and bankers, Sarasvathy et al. (1998) found that entrepreneurs tend to consider risk to be exogenous while concentrating on ways to control outcomes. In experiments in which participants were presented with scenarios with varying levels and distributions of financial returns, entrepreneurs "seemed to select the project with the best worst-case scenario.... They also expressed confidence that they could make the reality better than the worst-case probability calculated ex ante" (pp. 212–213).

These studies suggest that overoptimistic perceptions of success are more pronounced among start-up founders than managers of established firms. As a result, start-up firms may experience a lower incidence of successful market entry than established firms. This leads to our first hypothesis:

Hypothesis 1. *Entrepreneurial start-ups will be less likely to successfully commercialize inventions than established firms.*

Entrepreneurial overconfidence may continue after a new venture has been launched (Cooper et al. 1988, McCarthy et al. 1993). Cooper et al. surveyed 2,994 entrepreneurs heading newly founded ventures about their outlook for success. Entrepreneurs were asked (a) "What are the odds of your business succeeding?" and (b) "What are the odds of any business like yours succeeding?" The authors found that entrepreneurs often perceived the odds of their own venture's success to greatly exceed their own estimate of the chances of success for similar ventures. These findings suggest that founders of recently established firms often perceived the prospects for their own entrepreneurial ventures to be higher than was warranted by a more objective assessment or by comparison with historic rates of new venture success.

Shane and Stuart (2002) highlight that many university entrepreneurs rely heavily on advisors for financing, market assessments, product development, and other commercialization inputs after the start-up has been founded. Yet counsel from outside advisors often may do little to temper entrepreneurial overoptimism. For example, Suen (2004) demonstrates through a Bayesian updating process that preference by biased decision makers for advisors who share the same preferences and beliefs perpetuates (and even increases) such bias. Moreover, due to the difficulty in evaluating and transmitting specialized information to the decision maker, specialists often must summarize this information. Suen shows that if such "coarse information" is communicated by a neutral advisor, entrepreneurial use of simplifying heuristics will likely cause this information to be employed in a self-serving way.

These studies suggest that entrepreneurial overconfidence is unlikely to diminish once the firm has been founded, leading to our second hypothesis:

Hypothesis 2. *Start-ups will be less likely to terminate development efforts than established firms.*

Biased entrepreneurs may not only be overoptimistic relative to established firm managers regarding the length of time necessary to produce a successful market introduction, they also may overestimate the expected level of returns. We therefore expect the realized economic returns to an invention to be lower at the margin for inventions licensed to start-ups relative to inventions licensed to established firms:

Hypothesis 3. *The level of returns to inventions licensed by start-ups will be lower than the level of returns to inventions licensed by established firms.*

3. Data and Methodology

3.1. Sample Construction

We now turn to the empirical tests of our three hypotheses. We examine 734 inventions disclosed to the University of California (UC) from 1981 to 1999 and licensed exclusively to a firm. UC is one of the largest licensors of university technologies in the United States (AUTM Licensing Survey: FY 2002 (2003)). In 70 cases (9.5% of the sample) inventions are licensed at different times by different firms. For example, Firm B may license invention i after Firm A terminated a prior license of the same invention. Our unit of analysis is, therefore, a "license-invention pair."[2]

We define a start-up as a firm founded one year prior to or subsequent to the execution date of a license to commercialize a technology within our sample. We identified start-ups through phone contacts and interviews of employees at licensee firms and the university Office of Technology Transfer (OTT). This effort was supplemented by secondary sources to verify the accuracy of interviews. More than 75% of the inventions in this sample licensed by start-ups also

[2] One concern is that a start-up firm may benefit from more favorable licensing terms than an established firm, making it less costly for the start-up to hold a license (particularly if an established firm has earlier reviewed and rejected the licensed technology).

Unfortunately, we are not able to observe the contractual terms for the technologies licensed in our sample. We analyze contractual provisions reported by Elfenbein (2004) for licensed Harvard University inventions, however, and report our analysis in the online appendix to this paper (see http://mansci.pubs.informs.org/ecompanion.html). We find little evidence that small firms receive more favorable terms than large firms when licensing university technologies included in his study.

Table 1 Survival Outcomes by Licensee Type (Start-ups vs. Established Firms)

	Total ($n = 734$)	Start-ups ($n = 267$)	Established ($n = 467$)
Commercialized			
Count	188	75	113
% of total (%)	25.6	28.1	24.2
Abandoned			
Count	290	72	218
% of total (%)	39.5	27.0	46.7
Censored			
Count	256	120	136
% of total (%)	34.9	44.9	29.1

were reviewed by established firms either sponsoring the research or through nondisclosure agreements with the opportunity to license. Thirty-six percent of the inventions in our sample were licensed by start-up firms, with established firms licensing the remainder. Table 1 reports the distribution of inventions by whether the licensee is an established firm or a start-up.[3]

Firms often license an invention from UC before the invention has been patented, anticipating that a patent will subsequently be granted. In some cases, these licensees terminate the license prior to patent issuance. Sampling only on patented inventions, therefore, would overstate the rate of successful commercialization because these terminated licenses would not enter the sample. Moreover, established firms licensing inventions in our sample are more likely than start-ups to terminate a license prior to patent issue, thus biasing results in favor of established firms. Using the patent as the unit of analysis also may introduce "double-counting" because many inventions are associated with more than one U.S. patent. Biomedical inventions in particular can be associated with multiple patents. The number of patents per invention in our sample ranged from 0 to 16 with a mean of 1.83 patents. Of the 18 inventions generating 6 or more patents, all of them were in biomedical fields. To mitigate these selection biases, our sample includes both patented and unpatented inventions (although in two regression models we examine the subsample of patented inventions).[4]

These data allow us to identify the relative performance of start-ups and established firms commercializing similar inventions and observe the development and commercialization of licensed inventions. Contractual obligations include payment of minimum royalties and submission of periodic progress reports demonstrating active commercialization efforts. Failure to comply with these provisions ultimately results in license termination by the university. More commonly, we observe failed efforts when a licensee terminates the agreement after deciding not to pursue the technology further.

3.2. Measurements of Project Survival

As discussed above, a license represents an effort by a firm to develop and ultimately commercialize the licensed invention. At the end of our observation period, each license has one of three mutually exclusive outcomes:

(1) "Commercialized" (licensed with commercial sales), 188 cases (26% of sample).

(2) "Terminated" (licensed but contract was subsequently cancelled or ended prior to sales), 290 cases (40% of sample).

(3) "Censored" (licensed but no commercial sales nor license termination), 256 cases (35% of sample).

We characterize inventions within outcome (1) as those for which the firm has paid royalties to the university based on achieving product sales. Outcome (2) includes inventions for which the license was cancelled, thus signalling that the licensee has discontinued development and commercialization of the technology. Outcome (3) observations reflect active (nonterminated) licenses that have not reported commercial sales by the time the end of the sample period was reached in December 2002, and therefore are censored.

UC has historically followed a practice of initiating a patent filing only after potential licensees have demonstrated commercial interest. As a result, the patent filing date most closely reflects the commencement of the commercialization process. Although not every invention is associated with an issued patent (because a license may be terminated prior to the patent issue date), each licensed invention is associated with a patent application (or an approval to file a patent). We use the patent application or approval to file date to commence each spell in our duration models.

3.3. Measurement of Economic Returns

Because many firms in the sample are not public and do not report product-line sales or costs

[3] The distribution of established firm and start-up licensees by the nine University of California campuses is reported in the online appendix.

[4] Sampling only on patented inventions may introduce additional biases. Technology areas or industries in which patents are less effective for technology transfer, product development, or commercialization may be underrepresented. Prior research on university licensing has shown that licenses tend to be concentrated in areas where patents are the best means of protecting the returns to innovation, namely, biomedical technologies (Mowery et al. 2001, Shane 2004). In our sample, 16% of the licensed inventions disclosed between 1980 and 1997 were unpatented within five years.

related to these sales, we are unable to observe economic returns for these licensees directly. We therefore proxy for economic returns by the royalty payments received by the university as specified in the licensing agreement. University licensing contracts typically specify a royalty based on a percentage of sales (Jensen and Thursby 2001). License revenues have previously been used to estimate the private value of university inventions (Sampat and Ziedonis 2004).[5]

A challenging aspect to coding royalty data is to correctly categorize licensed inventions that received minimum royalties. Most contracts specify that the licensee pay the minimum of either a fixed dollar amount (minimum royalty) or a percentage of total sales (earned royalty). If sales are below a specified level but above zero, commercialization has occurred and the licensee pays the minimum amount. If total dollar sales are zero, the licensee pays the same minimum royalty, but the invention has yet to be commercialized. In the latter case, we assume that the firm anticipates future sales because it had not canceled or renegotiated the license. Of the inventions in our sample, 17.5% generated a minimum royalty but no additional earned royalty. We code royalty payments under the following decision rules: (1) licensed inventions for which a minimum royalty was paid but the license was subsequently terminated are coded as terminated on the date of termination (in this instance we assume that the minimum royalty does not represent actual sales, but signifies an effort to continue development), and (2) inventions generating a minimum royalty and a subsequent earned royalty are coded as commercialized on the earliest date of minimum royalty. We assume that the latter inventions were commercialized, but the initial sales were below the level specified for the minimum royalty payment.[6]

[5] A sales-based royalty measure would overstate profit for firms or industries that have considerable development costs relative to revenue. To the extent that university licenses to such industries are more likely to be executed to large firms because start-ups are less likely to have access to the considerable necessary capital, such a bias would work against a finding that start-up firms perform as well as established firms.

[6] The integrity of our data relies on the timeliness and accuracy of licensees reporting sales and making royalty payments. Unfortunately, we are not able to observe instances where the licensee terminates an agreement and discontinues payments to the university but continues development and commercialization activity. Shane (2002) points out that established firms may license an invention to learn about the technology or obtain related knowledge, but subsequently terminate the license without intent to commercialize. The likelihood of such behavior should be low because licensing is often a repeated game among inventors, the university, and outside firms. Continued commercialization after license termination invites legal action if discovered and would preclude future licensing opportunities with the university. In any case, should this bias be present it would be limited to the influence that active commercial efforts have toward license termination.

4. Analysis

4.1. Nonparametric Survival Analysis

We first examine the hazards of commercialized and terminated inventions using Kaplan and Meier's (1958) nonparametric product limit estimation. The Kaplan-Meier method provides a descriptive view of the overall survival functions, allowing us to unconditionally compare start-up and established firm licensees over time (thus serving as a summary statistic).

We calculate the probability of occurrence of an event (e.g., commercialization) on a given day based on the number of events occurring, E, and the number of observations at risk, R, at time t_l. The Kaplan-Meier procedure generates a step-function estimate of daily survival and is particularly useful for these data because more than one-third of the observations are censored. This estimator, $\widehat{H}(t)$, is expressed as[7]

$$\widehat{H}(t) = \Pi_{l|t_l<t}\left(1 - \frac{E_l}{R_l}\right). \tag{4.1}$$

Our sample frame begins with licenses executed in 1981 (which includes inventions disclosed in 1980) and ends in December 2002. The maximum survival time of an invention is 7,585 days (20 years, 9 months).

An observation is removed from the at-risk pool due to the occurrence of another event (i.e., termination) or censoring. For example, in the estimation of the hazard of commercialization, inventions that were terminated are coded as censored at 7,585 days. The intuition behind this coding scheme is as follows: Our analysis estimates the probability that an invention i will be successfully commercialized by firm j in time t. A termination is an event that signifies invention i will never be commercialized by firm j during any period. By keeping these terminated observations in the risk set throughout the process, we more precisely estimate the overall probability of commercialization. The alternative scheme, coding terminated licenses as censored on the date of termination, would understate the pool of inventions that could have otherwise been commercialized, biasing the estimation upward.[8] (The hazard of termination model employs a similar methodology, with observations removed

[7] For constructing confidence intervals in the analysis, standard errors of the survival function are calculated by applying Greenwood's method (Blossfeld and Rohwer 1995):

$$SE(\widehat{H}(t)) = \widehat{H}(t)\left[\sum_{l|t_l<t} \frac{E_l}{R_l(R_l - E_l)}\right].$$

[8] An additional technical consideration in the hazard of termination models is the treatment of inventions for which a minimum royalty was paid, but no other information on first sale or license termination exists. As discussed earlier, we code these inventions as commercialized on the date of minimum royalty payment in the

Figure 1 Kaplan-Meier Survival Estimates for Hazard of First Commercial Sale

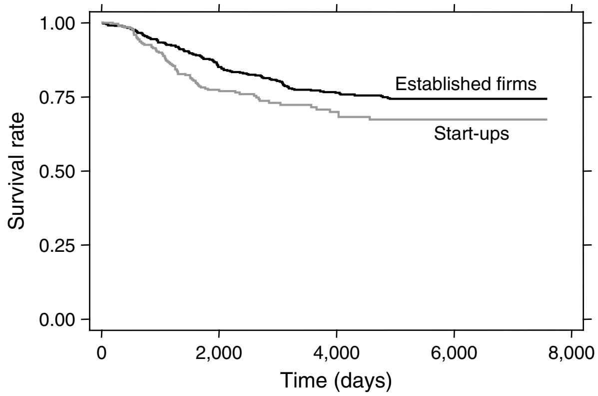
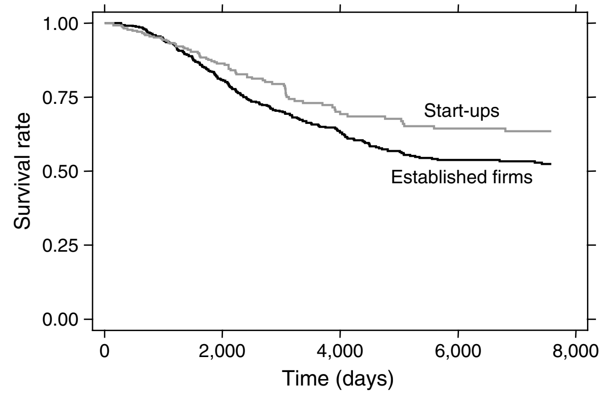


Figure 2 Kaplan-Meier Survival Estimates for Hazard of Project Termination



from the risk pool if the invention is commercialized or by censoring.)

Figure 1 plots the estimated commercial sale survival functions for start-ups and established firms. In this analysis, we estimate the likelihood that an invention exits the sample due to reaching a first commercial sale among those inventions at risk to have a commercial sale. The survival rate for commercialization for start-up firms is below the corresponding rate for established firms throughout virtually the entire time series, indicating that inventions licensed by start-ups are more likely to achieve a first sale (whereby they exit the sample) than inventions licensed by established firms. Based on tests that the two hazard functions are equal at time t (Tarone and Ware 1977), we can reject that the survival functions for commercialization of technologies for start-ups and established firm licensees are identical ($P > \chi^2 = 0.013$).[9]

Figure 2 plots the corresponding rates for license termination. We estimate the likelihood that a firm exits the sample due to terminating a license. The survival rate for licenses to start-up firms exceeds the rate for licenses to established firms throughout the period, indicating that start-up firms are less likely to terminate a license than are established firm licensees at any time t. The Tarone-Ware test statistic indicates that these survival functions are significantly different ($P > \chi^2 = 0.018$).

The Kaplan-Meier product limit estimation shows that for our sample, at any time t, start-ups are more likely to achieve a first sale for a licensed invention than are established firms, while being less likely to abandon commercialization efforts and terminate the license. We have not yet controlled for factors that may influence these survival functions, but these preliminary estimates suggest that, contrary to Hypothesis 1, start-up firms may be at least as effective in commercializing technologies arising from university research as established firms. We explore this possibility further in the next section.

4.2. Parametric Survival Analysis

The Kaplan-Meier estimation, while informative, does not allow us to examine some of the factors that may account for the differences in commercialization outcomes between start-ups and established firms. In this section, we undertake a parametric analysis that controls for time, location, and technology effects that may underpin the above findings.

We specify a survival estimation with a Gompertz distribution to capture the effects of time dependence in our models. The estimation is based on the following hazard function for time t (Blossfeld and Rohwer 1995): $H(t_\ell) = e^{X\beta+\gamma t_\ell}$. γ is an estimate of the overall hazard function over time based on the data. In each of our regressions γ is positive, reflecting that hazard rates are monotonically increasing with time.

The vector X consists of our primary variable of interest, *START-UP*, plus control variables. *START-UP* $= 1$ if the licensee is a start-up and 0 otherwise. Hypothesis 1 predicts that start-ups are less likely to achieve commercial success; in other words, that the coefficient for *START-UP* in the commercialization model will be less than one. Hypothesis 2 predicts that start-ups are less likely to terminate a license, or the coefficient for *START-UP* in the termination model will be less than one.

We condition these analyses on three classes of control variables. First, we include dummies for the year of invention disclosure to capture time-specific effects

hazard of commercialization analysis. In the hazard of termination models, however, we consider observations with only minimum royalties reported as censored on the last date of the sample frame, December 31, 2002, rather than at 7,585 days because we have no information for these observations beyond that date.

[9] We found similar results when employing different weighting of events over time using the log-rank and Wilcoxon statistics (not reported).

not assumed by the Gompertz model.[10] Second, we include a dummy variable for each inventor's campus to capture campus or geographic effects. We recognize inventions made by multiple inventors at different campuses by including a dummy variable for each inventor's campus.

We also control for technology field effects. Previous studies of university start-ups have controlled for technology field by aggregating U.S. patent classifications into five broad areas (Shane 2002) or by using international patent classes (Lowe 2002). Because our sample includes inventions for which patents have not been issued, we are unable to use such patent-based controls. We therefore use each inventor's primary academic department appointment as our control.[11]

Table 2 reports the results of regressions for the competing risks of commercialization and termination of inventions licensed by start-ups and established firms. Coefficients with hazard rates are displayed in brackets and z-statistics are displayed in parentheses. Models 1a and 1b include only a dummy variable for start-ups as a covariate. Model 1a reports a hazard rate for commercialization greater than one (1.40) at a 5% level of significance. Similarly, Model 1b reports that the hazard rate for termination is significantly less than unity (0.70), indicating that start-up firms are less likely to terminate a license than are established firms. These base models are equivalent to our earlier unconditional Kaplan-Meier analyses.

In Model 2a, controlling for inventor campus and department, the difference in hazard rates for commercialization by start-ups and established firms becomes nonsignificant (1.13). This result does not support Hypothesis 1, that start-ups exhibit a lower likelihood of initial success than do established firms. Start-ups and established firms are equally likely to commercialize inventions generated by the same university department.[12]

Table 2 **Competing Risk Models of Commercialization and Termination**

	(1a) Commercialized	(1b) Terminated	(2a) Commercialized	(2b) Terminated
Start-up	0.34 [1.40] (2.24)**	−0.36 [0.70] (2.62)***	0.13 [1.13] (0.65)	−0.52 [0.60] (3.12)***
Berkeley			−0.88 [0.41] (1.43)	0.20 [1.22] (0.37)
Davis			−0.60 [0.55] (0.97)	0.35 [1.48] (0.73)
Irvine			−0.38 [0.69] (0.61)	−0.46 [0.63] (0.77)
Los Angeles			−1.43 [0.24] (2.52)**	0.82 [2.27] (1.85)*
Riverside			−0.97 [0.38] (1.10)	0.55 [1.73] (0.69)
Santa Barbara			−0.87 [0.42] (1.13)	0.10 [1.10] (0.15)
San Diego			−1.29 [0.28] (2.42)**	0.38 [1.46] (0.87)
San Francisco			−2.06 [0.13] (3.86)***	0.73 [2.08] (1.71)*
Year dummies			Yes	Yes
Inventor's department			Yes	Yes
Constant	−9.06 (74.88)***	−8.96 (87.77)***	−8.03 (9.46)***	−8.95 (14.89)***
χ^2 test statistic	4.90**	7.23***	177.56***	186.47***

Notes. Coefficients reported with hazard rates are in brackets and absolute values of z-statistics are in parentheses.
Observations = 734.
*Significant at 10%; **significant at 5%; ***significant at 1%.
χ^2 test statistic refers to the test that all coefficients are jointly zero.

[10] Licensing to start-up firms became more prevalent at U.S. universities, including UC, during the 1990s (AUTM Licensing Survey: FY 2002 (2003)). If much of the start-up licensing activity occurred at the end of our sample period, there could be a concern that most start-up observations would be right censored and that our results were based on little information. However, the earliest start-up license in our sample period was executed in 1984. Moreover, by 1992, at least a third of all licenses executed each year were to start-up firms. Table 1 reports that less than half of all start-up observations are censored by the end of 2002.

[11] The number of forward citations is a commonly used measure of a patent's "quality." We do not control for invention "quality" using citations-based measures, however, because forward citations may be endogenous to successful commercialization of the underlying technology. Commercialized inventions may receive more citations merely by the fact that others in the field are more aware of the commercialized technology than they would be if the technology did not reach the market, a "publicity effect" (Lanjouw and Schankerman 1997). Moreover, for successfully commercialized inventions, the licensee may be more likely to generate follow-on patents that would cite the licensed patent than for those that are not commercialized. For our sample, therefore, being licensed is a better indicator of ex ante quality of an invention, while forward citations better predict ex post development and commercial success.

Consistent with a "publicity effect" for commercialized inventions in our sample, the median number of citations to commercialized patents, conditional on being licensed, is significantly greater than the median number of citations to terminated patents, even when citations made by the licensee are excluded. This result is posted in the online appendix.

[12] This result is consistent with earlier findings that technology field differences partially explain the occurrence of start-up foundation. Shane (2002) and Lowe (2002) found that start-ups are more likely

In Model 2b, we examine the likelihood of termination using the same control variables as in Model 2a. The hazard rate for termination by start-ups remains below that of established firms (significant at the 1% level), supporting Hypothesis 2 that entrepreneurs will hold projects longer than will established licensees. This suggests that entrepreneurial overconfidence may be manifested as a confirmation bias (Wason 1968) and is consistent with the Cooper et al. (1988) findings that entrepreneurs often remain overconfident after the venture has been founded.[13]

An alternative explanation for the difference between start-ups and established firms in the time they take to terminate licenses is that start-ups are more likely to pursue technology commercialization in fields that are closely related to scientific or "basic research" (Shane 2002, Lowe 2002) and that inventions in these areas require longer time for development.[14] To explore this possibility, we control for the scientific nature of inventions using the *SCIENCE* variable proposed by Trajtenberg et al. (1997). *SCIENCE* measures the level of scientific or basic research underlying a patented invention by calculating the proportion of all patent citations that are to journal articles. The greater the fraction of all citations made to journal articles, the more heavily the patent is considered to be based on basic research.

We can only examine the effect of *SCIENCE* on the 351 patented and licensed inventions in our sample. Models 3 and 4 in Table 3 test whether the scientific characteristic of inventions accounts for the likelihood of termination among start-ups. Model 3 is analogous to Model 2a and includes only the *START-UP* dummy variable and *SCIENCE*. Model 4 includes the full set of control variables and is analogous to Model 2b.

Including *SCIENCE* does not substantively alter our estimates of the likelihood to terminate development efforts for this subsample. The hazard rate is slightly lower for *START-UP* (0.45 versus 0.61 in regressions without *SCIENCE*).[15] This suggests that technology field differences between start-ups and established firms do not explain the differences in termination rates.

Table 3 Survival Analysis of Termination

	(3)	(4)
Start-up	−0.50	−0.80
	[0.61]	[0.45]
	(2.36)**	(2.92)***
Science	0.26	0.40
	[1.30]	[1.49]
	(1.05)	(1.12)
Campus		Yes
Year dummies		Yes
Inventor's department		Yes
Constant	−9.22	−9.07
	(44.68)***	(10.85)***
χ^2 test statistic	6.44**	142.45***

Notes. Sample only includes 351 inventions between 1986–1995 that were patented. Coefficients reported with hazard rates are in brackets and absolute values of z-statistics are in parentheses.
Observations = 351.
*Significant at 10%; **significant at 5%; ***significant at 1%.
χ^2 test statistic refers to the test that all coefficients are jointly zero.

Perseverance by start-ups in developing university inventions is not explained by technology area, geographic factors, or the scientific nature of the invention. Although not conclusive, this result is consistent with the view that entrepreneurs are overoptimistic about their chances for success as time proceeds and commercialization has yet to be reached. The result is also consistent with rational explanations for entrepreneurial persistence, a point we return to in §5.

4.3. Licensing Revenues

Our third analysis examines whether inventions commercialized by start-ups generate greater or lesser revenues than do those commercialized by established licensees. We consider only those technologies that are commercialized, excluding terminated and censored observations. Recall that Hypothesis 3 predicts that average returns generated by inventions developed by entrepreneurial firms should be lower than inventions developed by established firms.

Because the distribution of royalties is truncated on the left at zero, following Shane (2002) we employ a

in technology fields where technical knowledge underlying the invention is more tacit. Lowe (2002) found that university start-ups tend to license inventions that result from research that is oriented towards basic science.

[13] In a study of French entrepreneurs, Landier and Thesmar (2003) found that entrepreneurs developing their own ideas were significantly more likely to be overoptimistic regarding their ventures' likelihood of success than entrepreneurs that took over or inherited existing firms. To test whether inventor-founded firms performed differently than non-inventor-founded firms in our sample, we conducted the commercialization and termination analyses reported in Models 2a and 2b of Table 2 considering only inventor-founded firms. We found no qualitative difference from the reported findings.

[14] On the other hand, overconfidence may be most pronounced in basic research because criteria for success are less well defined, leading to optimism promoted by ambiguity (Camerer and Lovallo 1999).

[15] Limiting the sample to patented inventions introduces bias to our analysis by disproportionately removing licenses terminated by established firms rather than start-ups. This decreases the higher termination rate more among established firms to a rate closer to the start-up termination rate. However, the patent bias works against our findings in Models 3 and 4.

Table 4 Tobit Regressions of the Natural Log of University Earnings

	(5)	(6)	(7)
Start-up	0.55	0.89	1.04
	(1.71)*	(2.65)***	(3.12)***
Berkeley			−0.21
			(0.19)
Davis			−0.16
			(0.15)
Irvine			−1.23
			(1.11)
Los Angeles			−0.92
			(0.93)
Riverside			3.05
			(1.77)*
Santa Barbara			−0.34
			(0.25)
San Diego			−1.47
			(1.56)
San Francisco			−1.38
			(1.61)
Inventor's department	Included in Models 6 and 7		
Year dummies	Included in Models 5 and 7, see notes below		
Constant	14.17	14.88	17.08
	(12.52)***	(12.32)***	(11.57)***
Pseudo-R^2	0.07	0.16	0.18
χ^2 test statistic	57.55***	138.49***	154.81***

Notes. Absolute value of t-statistics are in parentheses.
Observations = 188.
*Significant at 10%; **significant at 5%; ***significant at 1%.
χ^2 test statistic refers to the test that all coefficients are jointly zero.

tobit analysis of total royalties and fees paid to the university related to a commercialized invention.[16] A few inventions in our sample generate extreme positive values ("home runs"), resulting in a skewed revenue distribution. We use the natural log of payments to the university as our dependent variable to normalize this distribution.

Results are reported in Table 4. Model 5 includes only the *START-UP* dummy variable. Model 6 incorporates the effect of time and technology area (inventor's department), and Model 7 includes the inventor's campus.

We find that in the base model (Model 4) licenses to start-ups generate greater earnings than do inventions licensed to established firms, but these results are weakly significant (at the 10% level). The coefficient for *START-UP* is 1.04 in Model 7 and is significantly different from zero at the 1% level. Based on licensing revenue, these results suggest that start-ups outperform established firms, refuting Hypothesis 3.

[16] Our sample and analysis differs from Shane (2002), however, because he examined returns only to established firm licensees and we compare royalties generated by both start-ups and established firms.

5. Discussion

In this paper, we explore commercialization outcomes of university technologies licensed by start-up firms based on the time to first sale, time to license termination, and level of license revenues. Utilizing a novel data set of almost two decades of licensing activity at the University of California, we compare the relative performance of start-ups and established firms in commercializing inventions discovered in the same university departments. We find little difference between start-ups and established firms in the time it takes to develop and introduce to the market a product based on a licensed invention. We also find that start-ups generate greater levels of licensing revenues for similar technologies than do established firms. These findings are particularly interesting because vulnerability to random environmental shocks due to early age and small size, the liability of newness (Stinchcombe 1965), or difficulty accessing complementary assets often make start-ups prone to failure. Against a backdrop of such threats, a finding that start-ups meet and even surpass established firms in these dimensions of firm performance is inconsistent with a hypothesis that university entrepreneurs overvalue commercialization opportunities prior to founding a firm.

We do, however, find some support for an ex post version of the overoptimism hypothesis: Relative to established firms, entrepreneurs appear to hold on longer to technologies that do not achieve commercial success—entrepreneurs may be "in denial" about their diminishing prospects for these inventions. While suggestive, this evidence is not sufficient for us to conclude that entrepreneurs are overoptimistic in the pursuit of these technologies. For example, as long as the marginal expected benefit of continuing development is greater than the marginal cost, it would be rational to continue development, even for technologies that eventually fail. Moreover, the expected benefit may exceed expected cost at the margin regardless of whether the initial forecasts by the decision maker are overoptimistic (Camerer and Weber 1999). Programs favoring entrepreneurs such as public funding programs for start-ups (Lerner 1999), funding of university ventures by government agencies (Lowe 2001), or equity arrangements by universities (Feldman et al. 2002) may allow university start-ups to enjoy lower costs than existing firms in licensing and continuing development. That start-ups do achieve commercialization at a pace and level of existing firms overall suggests that it may make sense for entrepreneurs to continue development, even for those technologies that ultimately fail. On the other hand, established firms may have greater opportunities to use development resources than start-ups and thus impose a higher threshold for continuing development projects.

Established firms may also be able to employ resources towards development at a greater rate than can start-ups, enabling them to obtain information on the viability of the licensed technology more quickly. This may also explain the finding that established firms terminate licenses more quickly than do start-ups for technologies that eventually fail to reach the market. Case studies of start-up commercialization of university technologies by Lowe (2001), however, suggest that start-ups may invest more heavily in the early stages of technology development than established firms because they are under greater pressure to produce initial results such as prototypes, test data, or proof of concept to attract investment capital or research funding.

Unfortunately, we are unable to observe the development costs and benefits by licensees that would allow us to control for these factors. To explore this issue further with data that we can observe, we constructed 10-year "commercialization histories" of the 43 inventor-founded start-ups in the sample. Table 5 reports all inventions between 1986 and 1995 licensed to inventor-founded start-ups and includes the start-ups' operating status as of June 2002 (operating independently, defunct, or acquired by an established firm).

Virtually all inventor-founded start-ups that commercialized an invention were acquired, and all but two of these firms were acquired prior to commercialization. Most unacquired firms remain in product development with no significant sales. Note that the greatest return to UC among the independent start-ups was realized through the proceeds of an initial public offering, not from royalties based on commercial sales. The results reported in Table 5 indicate that start-ups and established firms may operate as complementary, rather than substitute vehicles for commercialization of some technologies in university licensing.

As Shane (2002) points out, established firms often have a competitive advantage in commercializing inventions. Conversely, inventors often have a comparative advantage in development when the knowledge necessary to further develop the invention is largely tacit (Shane 2002, Lowe 2006). Table 5 suggests that considering commercial outcomes such as time to first sale or termination of licenses without a more detailed examination of the mode of commercialization reveals only part of the entrepreneurial story. There appears to be a delicate balance between established firms' comparative advantage in commercialization, through superior access to complementary assets, resources, and market knowledge, and inventors' comparative advantage in developing early-stage technologies.

Entrepreneurs function within a "market for ideas" and may choose a strategy of "competition" or "cooperation" with established firms (Gans and Stern 2000, Gans et al. 2002). Once they have licensed a university technology, entrepreneurs are not locked in over time to pursuing commercialization on their own, but may later choose to cooperate, via joint venture, acquisition, or other linkages with established firms. Without the entrepreneurial role of the inventor-founder however, some technologies would be left to languish, or licensed by established firms and unsuccessfully commercialized, as illustrated by our first two introductory examples. Thus, inventor-founded firms may serve a transitional organizational form in the market for technology commercialization and this division of labor—development in start-ups, commercialization in established firms—contributes to a "first-best" outcome from a longer-term perspective.

Our study is not without its limitations. Beyond technology and location dummies, we do not control for more detailed characteristics of the inventions licensed other than department and campus of origin. Although our department controls are rough proxies for differences among technological fields, incorporating more precise measures of differences in appropriability, patent effectiveness, and technological opportunity across technical fields might improve our analysis. Moreover, the findings from this study are based on licensing activity at a single institution, UC. The two studies closest to ours utilize data from MIT (Shane 2002, Dechenaux et al. 2003). Shane's (2002) finding that start-ups are more likely to terminate a license than an existing firm contradicts our result, but it is unclear whether this disparity is due to dissimilar licensing practices between UC and MIT or other systematic differences between the technologies or licensees in our respective data sets. It is also uncertain whether Shane's conclusion that licensing university technology to start-ups represents a "second-best solution" would hold if he considered a longer postlicense time frame and possible acquisition activity. A more recent examination of licenses to MIT inventions reveals results closer to those of our study. Dechenaux et al. (2003) conduct an event-history analysis of time to first sale and contract termination using a sample comparable to ours (patents issued between 1980 and 1996). Consistent with our findings, they find that start-ups are as likely as established firms to reach a first sale. On the other hand, they find little evidence that start-ups take longer to terminate a license than do existing firms. To test the influence of institution-specific factors on the licensing of university inventions, future research should

Table 5 Royalties by Inventor-Founded Firms at the University of California on Inventions Disclosed Between 1986–1995

Industry	Ownership	Product status	(a) Earned + minimum + milestone ($)	(b) Earned + minimum ($)	(c) Earned royalties ($)	(d) Royalties on final products
1 Biotechnology	Acquired	Commercial sales[1]	305,386.72	305,386.72	305,386.72	Y
2 Pharmaceuticals	Acquired	Commercial sales	1,013,735.38	1,013,735.38	1,013,735.38	Y
3 Medical devices	Acquired	Commercial sales	13,000.00	13,000.00	—	N
4 Medical devices	Acquired	Commercial sales	287,549.93	267,549.93	267,549.93	Y
5 Pharmaceuticals	Acquired	Commercial sales	91,249.07	26,249.07	26,249.07	Y
6 Biotechnology	Acquired	Commercial sales	17,851.02	17,851.02	17,851.02	Y
7 Pharmaceuticals	Acquired	Biotech tool integrated in parent's platform	75,000.00	—	—	N
8 Advanced materials	Acquired	Commercial sales	525,000.00	525,000.00	100,000.00	Y
9 Biotechnology	Acquired	Commercial sales	140,945.32	140,945.32	945.32	Y
10 Pharmaceuticals	Independent	In development	—	—	—	N
11 Advanced materials	Independent	In development	—	—	—	N
12 Pharmaceuticals	Independent	In development[2]	85,752.00	85,752.00	85,752.00	N
13 Pharmaceuticals	Independent	Early clinical trials	—	—	—	N
14 Medical devices	Independent	In development	—	—	—	N
15 Computer hardware	Independent	Working prototype	—	—	—	N
16 Pharmaceuticals	Independent	Early clinical trials	—	—	—	N
17 Medical devices	Independent	In development	—	—	—	N
18 Pharmaceuticals	Independent	Early clinical trials	—	—	—	N
19 Biotech/pharmaceuticals	Independent	Early clinical trials	—	—	—	N
20 Biotech/pharmaceuticals	Independent	Stem cell registry, clinical trials	10,000.00	10,000.00	—	N
21 Pharmaceuticals	Independent	In development	—	—	—	N
22 Biotechnology	Independent	In development	—	—	—	N
23 Biotechnology	Independent	In development	—	—	—	N
24 Pharmaceuticals	Independent	Clinical trials	58,333.00	—	—	N
25 Medical devices	Independent	Commercial sales	2,100.00	2,100.00	2,100.00	Y
26 Pharmaceuticals	Independent	In development	6,000.00	—	—	N
27 Pharmaceuticals	Independent	Early clinical trials	—	—	—	N
28 Pharmaceuticals	Independent	In development	—	—	—	N
29 Biotech/pharmaceuticals	Independent	Early clinical trials	—	—	—	N
30 Pharmaceuticals	Independent	In development	—	—	—	N
31 Pharmaceuticals	Independent	In development	—	—	—	N
32 Biotechnology	Independent	Commercial sales/ sublicensing	80,000.00	80,000.00	—	Y
33 Software algorithm	Independent	Sublicensing	14,411.79	14,411.79	14,411.79	Y
34 Biotechnology	Independent	Early clinical trials	—	—	—	N
35 Biotechnology	Independent	In development	—	—	—	N
36 Computer hardware	Independent	In development	—	—	—	N
37 Medical devices	Independent	Commercial sales	—	—	—	N
38 Biotechnology	Independent	Research partnerships	—	—	—	N
39 Biotechnology	Independent	In development	—	—	—	N
40 Advanced materials	Defunct		6,000.00	6,000.00	—	Y
41 Biotechnology	Defunct		—	—	—	N
42 Test and measurement	Defunct		—	—	—	N
43 Biotechnology	Defunct		—	—	—	N

Notes. Royalties reported gross of delayed or installment payments through July 2002.
(1) Proportion ($272,450) of earned royalties is equity cash out.
(2) Entire $85,752 of earned royalties is equity cash out.

examine the role of start-ups across a broader cross-section of universities.

Another limitation of our study, in line with other recent studies of overoptimism among entrepreneurs, is the difficulty in disentangling overoptimism from rationality-based explanations for decision-making behavior. For example, Åstebro (2003) found that an overwhelming majority of Canadian inventors who submitted their ideas to a nonprofit inventors' assistance program for counsel on whether to pursue further development were advised to abandon commercialization efforts. Yet, half of the inventors receiving this recommendation continued development despite the fact that the ex ante probability of reaching the marketplace was only 4% and the median expected return, conditional on commercialization, was negative. Although such behavior suggests overoptimism, other explanations are equally compelling. Despite a low expected probability of success, the distribution of realized returns to invention in Åstebro's sample is highly skewed, much like that exhibited for university inventions. This suggests that inventor behavior may be driven by rational models of risk preferences or the skew distribution of returns rather than overoptimism.

The difficulty in identifying overoptimism among alternative explanations in decision making highlighted in our study and the Åstebro paper suggests that future research could seek more direct measures of overoptimism among individual decision makers. Malmendier and Tate (2005) identify personal characteristics of CEOs that are correlated with indirect measures of overoptimism in acquisition choices. Similarly, Barber and Odean (2001) find that gender differences are systematically related to levels of overconfidence in stock trading behavior. Less is known about how decision biases affect the process by which university technologies are commercialized.

Our findings nevertheless offer insight into the commercialization process of licensed university technologies. Entrepreneurs appear to "hold their own" relative to more established firms, particularly in the commercialization of early stage inventions requiring substantial technological development. Because a stated goal of most university technology transfer professionals is the development and introduction to the market products based on university research, our evidence suggests that the active pursuit of licensing to university start-ups is worthwhile.

An online appendix to this paper is available on the *Management Science* website (http://mansci.pubs.informs.org/ecompanion.html).

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