Do University Entrepreneurs Exhibit Cognitive Bias?

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Abstract

Recent theoretical and experimental research suggests that cognitive bias or Bold Forecasting is a critical influence on entrepreneurs' decisions. We examine whether cognitive bias appears to be a significant influence on entrepreneurial ventures using data on commercialization efforts for university inventions. We are able to separate the potential effects of cognitive bias at different stages of these entrepreneurial ventures. Our results indicate that while cognitive bias does not appear to be a prevalent determinant of the overall decision to found a firm, we find evidence of "denial bias": university entrepreneurs continue unsuccessful development efforts for longer periods of time than do established firms.

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1. Introduction

Academics characterize entrepreneurs as a peculiar group of individuals. Economic models have focused on risk tolerance as a critical characteristic of entrepreneurs (Kihlstrom and Laffont 1979). Recently scholars have suggested that observed risk tolerance among entrepreneurs merely represents cognitive bias in which individuals overvalue opportunities they are faced with (Kahneman and Lovallo 1993). Entrepreneurs may be susceptible to Bold Forecasts when they apply an "inside view," focusing narrowly on the unique details of a specific asset or opportunity rather than evaluating the potential of the asset or opportunity given its observable characteristics and the success rates of other projects with similar characteristics (Kahneman and Lovallo 1993). The latter description characterizes the rational process an outside analyst would use to evaluate an opportunity.

Bold Forecasts may be partially attributable to the observation that entrepreneurs analyze opportunities differently than managers in established firms because entrepreneurs apply a unique set of heuristics in decision-making (Busenitz and Barney 1997). Prior experiences unique to an entrepreneur also temper the set of opportunities entrepreneurs recognize for a given technology (Roberts 1991, Shane 2000).

Support for this theory has come almost exclusively from survey and experimental work. Cooper, Woo and Dunkelberg (1988) use the 1985 survey of the National Federation of Independent Businesses and found that entrepreneurs were strongly optimistic about their chances of success. Moreover, entrepreneurs' assessments of their potential were uncorrelated with typical independent predictors of success. Experimental research by Camerer and Lovallo (1999) demonstrated overconfidence among participants in games relying on their own skills. More importantly, this research found that overconfidence was stronger when individuals could choose to enter games that rely on their personal skills. This insight is important for the entrepreneurship literature because although there is considerable evidence demonstrating that individuals are overconfident in their decisions (Kahneman and Lovallo

1993), Camerer and Lovallo's results illustrate the selection process where individuals with greater overconfidence appear to be those who choose to enter a game, or more appropriately who chooses to enter an industry.

This research typically motivates the phenomenon of entrepreneurial cognitive bias by citing high failure rates among new businesses[1] (Cooper, Woo and Dunkelberg 1988). While we cannot directly measure an entrepreneur's level of cognitive bias, the connection between success rate and entrepreneurial overconfidence is clear. Overconfidence should lead entrepreneurs to invest in lower quality opportunities on the margin and thereby fail more often than outside investors evaluating the same opportunities.

However, such observations are biased by focusing solely on the failure rate of start-ups. These observations do not account for the comparative success rate of established firms pursuing individual development projects in the same technology area and geography. In short, experimental evidence, interviews and surveys, are clearly important for establishing the phenomenon and demonstrate the need for work examining entrepreneurial cognitive bias using "naturally occurring data," in the words of Camerer and Lovallo (1999).

In this paper, we test whether entrepreneurs exhibit cognitive bias in commercializing university inventions. We account for the counterfactual of established firms' performance by examining the success rates of start-ups versus established firms in developing and commercializing inventions licensed from the same university department. We analyze relative performance in three aspects of start-up success: likelihood of achieving commercial sales, likelihood of terminating a development effort, and economic returns to a developed invention. This approach allows for a much richer identification of how cognitive bias may affect an entrepreneurial venture than simply examining the failure rate of start-ups.

This richer identification yields important distinctions. Our results do not show evidence that entrepreneurial cognitive bias is an overriding factor in the decision to found a firm:

[1] See for example, Camerer and Lovallo (1999), Kahneman and Lovallo (1993), and Mehta and Cooper (2000).

entrepreneurial ventures exhibit *statistically equivalent* success rates to established firms in commercializing university inventions once one controls for narrowly defined technology areas, location, and time effects. In addition, licenses to start-ups yield economic returns at least as good as the returns for licenses to established firms.

However, we find strong evidence that start-ups continue unsuccessful development efforts for longer periods of time than do established firms. The rate of project termination is far lower for start-ups than established firms, and these results persist even after controlling for the scientific nature of projects. Our results suggest a "denial bias." Entrepreneurs still in development may be in denial about their real, limited chances for future success.

Our research offers several contributions to the entrepreneurship literature. First, this study is the first empirical examination, to our knowledge, of cognitive bias and entrepreneurial decisions using naturally occurring data, filling a significant gap in the entrepreneurship literature noted by several papers (Camerer and Lovallo 1999, Mehta and Cooper 2000). Second, the richer depiction of cognitive bias, characterizing different stages of development and commercialization, offers a theoretical contribution to the entrepreneurship literature in the concept of denial bias. This finding suggests a need for further research throughout the early life cycle of new organizations, since this form of cognitive bias would not be captured in examining birth and death rates in an industry.

Third, our research lends further support to previous research on why new firms are founded to commercialize university inventions (Roberts 1991, Lowe 2002, Shane 2000, Shane 2002). Although the primary focus in this paper is on cognitive bias among university entrepreneurs, complements a set of research that has examined how technological characteristics predict whether a start-up or established firm will license a university invention (Lowe 2002; Shane 2002). Our results are consistent with the theory that technological characteristics play a greater role than cognitive bias in the decision to found a firm to commercialize university technologies.

Finally, our research speaks to an economically important sample of firms, university start-ups, that raise substantial public policy questions. Federal and state governments as well as universities often devote public resources to encourage start-up activity. Universities have increasingly been willing to take equity positions in lieu of royalty payments for intellectual property licenses. In a 2000 survey, Feldman, *et. al.* (2002) found that 40% of research universities surveyed held equity investments in new firms licensing their technology.

An obvious policy concern is that public funds will be applied to investments with little hope of success. Individual cases have demonstrated substantial returns to universities. 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 equity in and a board seat at search engine company Lycos, both which issued IPO's during the boom of the late-1990's. Our results are more informative as a general characterization of university start-up performance. Our results show that universities licenses to start-ups have indeed been effective mechanisms for technology transfer and encouraging commercialization of university inventions.

In the next section we develop explicit hypotheses to test for cognitive bias. Section 3 describes the data and our methodology. Section 4 discusses the empirical analysis and results. We conclude the paper in Section 5.

2. Hypotheses

Cooper, Woo, and Dunkelberg (1988) found that new entrepreneurs significantly overstated their expected probability of achieving success relative to similar firms. This characterization of cognitive bias translates to the university environment as overestimating the probably of success in developing and commercializing a recently licensed technology. University entrepreneurs and established firms license inventions that require considerable additional development efforts, often requiring years of development, until they are able to be sold in the market (Jensen and Thursby 2001). Entrepreneurs may underestimate the difficulty or challenges involved and consequently overstate the likelihood they will be able to successfully develop a technology.

Analyzing licensing activity at MIT, Shane has examined several factors that encourage new firm formation, including opportunity recognition by entrepreneurs (Shane 2000). Shane demonstrates convincingly that the personal background of different entrepreneurs influences their perceptions about commercial application of the same invention. This argument is consistent with Kahneman and Lovallo's notion of Bold Forecasts to the extent that university entrepreneurs may focus their analysis on their particular backgrounds and experiences as well as the narrow details of the technology at hand rather than carefully examining the best opportunity given the market environment. Not surprisingly, a number of the examples in Shane's (2000) case studies appear to be failed attempts at commercialization.

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

Hypothesis 1 addresses cognitive bias that occurs *ex ante* to firm formation, where entrepreneurs are overoptimistic regarding their opportunities at the decision to found a firm. However, entrepreneurs may also be overoptimistic about their chances for success *ex post* to their decision to start a firm. As challenges arise throughout the process, inevitably some technologies will not be successfully developed to a product form that is suitable for the market. In such cases, established firms may be quick to terminate a license and move on to other opportunities.

In addition, an entrepreneur may be unable to access the necessary complementary assets (Teece 1986). An optimistic entrepreneur, however, will cling to a failing development project in spite of evidence suggesting that efforts are increasingly unlikely to bear fruit. In light of Kahneman and Lovallo and Cooper, Woo, and Dunkelberg's theses, entrepreneurs will continue to overstate their chances of success. As we referred to in the introduction, entrepreneurs holding failing development efforts may simply be in denial about their future chances.

Hypothesis 2. Start-ups will be less likely to terminate licenses to undeveloped inventions efforts than established firms.

Our third and final level of analysis tests cognitive bias in the economic returns to commercialization. Success for a start-up includes both survival, tested in Hypothesis 1, as well as total returns, among other goals pursued by university entrepreneurs (Roberts 1991). Bold Forecasting with respect to the value of an opportunity predicts that biased entrepreneurs will assign a higher expected return than an outside analyst (in this context, established firms) would. As a result, we expect the realized economic returns to an invention to be lower on the margin for inventions licensed to start-ups compared to inventions licensed to established firms.

Hypothesis 3. The returns to inventions licensed by start-ups will be less than the returns to inventions licensed by established firms.

3. Data and Methodology

3.1. Sample construction

The university setting offers a unique environment to examine the relative performance of start-ups and established firms commercializing similar inventions. First, data is maintained at the level of individual inventions, allowing us to compare success on specific development and commercialization efforts rather than overall firm survival. University data also has the advantage that outcomes are regularly and clearly measured. Success is captured through required royalty payments and reporting made to the university as part of a licensing contract. Failure to comply ultimately results in the university terminating a license. More commonly, however, failed efforts are captured when a licensee terminates the agreement after deciding not to pursue the technology further. Contractual obligations including minimum royalty payments, as well as the threat of legal recourse based in federal legislation[2], make it is costly for licensees to simply hold technology without either actively seeking commercialization or terminating the license.

We examine 734 inventions disclosed to the University of California between 1981-1999 and exclusively licensed to a firm. The unit of analysis is a license-invention pair since in 70 cases (9.5% of the sample), inventions are licensed at multiple times by different firms. For example, Firm B may license invention i after Firm A terminated a prior license of the same invention. Each invention-license observation represents an effort to develop and commercialize a technology based on one or more inventions. We restrict our analysis to exclusive licenses, rather than including non-exclusively licensed technologies, since the latter primarily represents research tools, assays and tests, and the like. Exclusively licensed products require little development and can presumably be incorporated more readily into an existing firm's research operations or products.

We define a start-up as a firm founded one year before or after executing a license to commercialize a technology within our sample. Start-ups were identified by contacting licensee firms and university employees by phone and personal interviews. This effort was supplemented by secondary sources to verify the accuracy of interviews. Thirty-six percent of the inventions in our sample were licensed by start-up firms with established firms licensing the remainder.

A particular characteristic of our university data makes it (perhaps uniquely) appropriate to identify relative success between start-ups and established firms in commercializing similar technologies. In previous work, we have found that over three-quarters of inventions

[2]Specifically, the Bayh-Dole Act grants title to federally funded research to universities and includes a "March-in" rights provision, 35 USC Sec. 203. This provision allows a federal funding agency to force the university or licensee to license the invention to another party if it is believed that the current licensee will not achieve commercialization in a reasonable timeframe or poses a health or safety risk. March-in rights were exercised in a very public case started in 1997 involving CellPro, Baxter Healthcare, and Johns Hopkins University.

licensed by start-ups were also reviewed by established firms either sponsoring the research or through non-disclosure agreements with the opportunity to license (Lowe 2002). In our discussions with licensing officers at UC, we found that approaching established firms first was common practice, largely due to the belief that established firms typically had better access to development resources. This environment offers a near ideal data generating process to capture the scenario of entrepreneurial cognitive bias since most start-ups in our sample are licensing inventions reviewed to some varying extents by established firms.

Our sample includes both patented and unpatented inventions. Many studies of university technology transfer, including some of our own work, have been limited by the necessity to examine only patented inventions. Patent data are attractive in studies of innovation because they are readily available and can be easily used to construct variables based on technology class, citations counts, and the like, but also may be misleading indicators of innovation if not carefully applied (Griliches 1990). In the present study, sampling only on patented inventions introduces several potential biases. First, technology areas or industries in which patents are perceived as less important for successful technology transfer, product development, or commercialization may be underrepresented. Prior research on university licensing indicated 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). Second, considering the patent as the unit of analysis introduces possible "double-counting" because many inventions are associated with more than one U.S. patent. Biomedical inventions in particular can be associated with a number of patents.

In results not reported in this paper, we find that sampling only on patented inventions overstates the rate of successful commercialization since a license may be terminated prior to patent issue and would never enter the sample frame of patented inventions. We find that this sampling process biases in favor of established firms since, compared to start-ups in our data, established firms are significantly more likely to cancel unsuccessful commercialization efforts earlier in the process (in many cases before the patent has issued). Therefore, our primary analysis includes both patented and unpatented inventions, although two regression models will only look at a subsample of patented inventions.

3.2. Measurements of project survival

For our examination, we categorize the outcome of a license for an invention as an event, in the sense of an event-history or duration model. Each outcome event is in one of three mutually exclusive states:

1. "Commercialized" (licensed with commercial sales, n=188; 25.6% of sample)
2. "Terminated" (licensed but contract was subsequently cancelled or ended prior to sales, n=290; 39.5% of sample)
3. "Censored" (licensed but no commercial sales nor license termination, n=256; 34.9% of sample)

Table 1 reports the distribution of inventions by whether the licensee is an established firm or a start-up. We identify inventions within State 1 as those for which the firm has paid royalties to the university based on achieving product sales. State 2 includes inventions for which the license was cancelled, thus signalling that the licensee has discontinued development and commercialization of the technology. We treat State 3 observations as censored. Inventions in this state include active (non-terminated) licenses that have not reported commercial sales. Therefore, neither a commercialization nor license termination event had occurred by the last time period in our analysis for these inventions.

For survival analyses, each spell begins on the patent application date and ends on the date a royalty payment was received (commercialized), the license was terminated, or the end of the sample period was reached (censored) in December 2002.

The University of California historically followed a practice of initiating a patent filing only after apparent, if not committed, commercial interest by potential licensees. This date most closely reflects the commencement of the commercialization process, therefore. As we note above, not every invention is associated with an issued patent since a license may be terminated prior to the issuance of a patent. However, each licensed invention *is* associated with a patent application (or an approval to file a patent), since firms are unwilling to pay licensing fees without the assurance of intellectual property rights to develop and market the invention.

3.3. Measurement of economic returns

To measure economic returns, we use royalty payments to the university specified in the licensing agreement. Licensing contracts specify a running royalty based on a percentage of sales be paid to the university (Jensen and Thursby 2001). Royalties are used in this paper because we are not able to observe commercial sales for each individual product because many of the firms in the sample are private companies and do not report product-line sales. Nonetheless, this analysis provides insight into the level of commercial success of inventions licensed by start-ups and generates an estimate of the economic value of commercial success within the sample.

A challenging aspect to coding university royalty data is how to treat minimum royalty payments that do not necessarily reflect product sales. 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 particular level, the licensee pays the minimum amount. In examining individual cases, we found that in some licenses the total dollar sales to date are zero, and the licensee paid the minimum royalty in anticipation that the product would still be commercialized. Since the firm did not cancel or renegotiate the license terms we assume that it anticipates forthcoming sales.

The challenge, therefore, is to correctly categorize licensed inventions that received minimum royalties. We cannot observe whether a minimum royalty payment represents the case of sales under the minimum amount (but commercialization has occurred) or simply no sales and hence the invention has yet to be commercialized.

This data challenge applies to a minority of inventions, but is non-trivial. Overall, 17.5% of the inventions generated a minimum royalty but no additional earned royalty. We seek to be conservative in our approach while still trying to best utilize the information we have on the current state of each invention. Therefore, we code royalty payments under the following decision rules: Licensed inventions for which a minimum royalty was paid but the license was subsequently terminated are coded as terminated on the date of termination. We assume that the minimum royalty was not indicative of actual sales, but an effort to continue development. Second, inventions generating a minimum royalty and a subsequent earned royalty are coded as commercialized on the earliest date of minimum royalty. We assume these inventions were commercialized, but the initial sales were below the level specified for the minimum royalty payment.

A second consideration is that the integrity of our data relies on the timeliness and accuracy of licensees reporting sales to the university for the purpose of determining 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[3]. We believe this concern to be minimal. University licensing is a repeated game to the extent that multiple relationships between inventors, the university, and outside companies should mitigate such behavior. Continued commercialization after license termination invites both legal action if discovered and would preclude future licensing opportunities with the university.

[3] Shane (2002) also suggests this possibility. He 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. We agree that such cases may exist. Our concern with this bias is limited to the effect that active commercial efforts have towards license termination.

4. Analysis and Discussion

4.1. Non-parametric survival analysis

We first examine the hazards of commercialized and terminated inventions using Kaplan and Meier's (1958) non-parametric product limit estimation. The Kaplan-Meier method provides a descriptive view of the overall survival functions, and allows us to unconditionally compare start-up and established firm licensees over time. Unconditional survival analysis serves primarily as a summary statistic of sorts– to better understand the data at a high level before controlling for technology factors in parametric analysis.

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 since over one-third of the observations are censored. This estimator, $\widehat{H}(t)$, is expressed as:[4]

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

Our sample frame begins with licenses executed in 1981 and ends in December 2002. The maximum survival time of an invention in the data is 7585 days (20 years, 9 months).

An observation exits the sample when it achieves a given event we are interested in. An observation is removed from the at-risk pool if the observation is censored before reaching the event. Inventions that experience another event precluding the event of interest (e.g., terminated licenses in our analysis of commercialization) are treated as censored observations for the duration of the sample frame. For example, in the estimation of the hazard of commercialization, inventions that were terminated are coded as censored at 7585 days.

[4] For constructing confidence intervals in the analysis, standard errors of the survival function are calculated by applying Greenwood's suggested method (Blossfeld and Rohwer 1995): $SE(\widehat{H}(t)) = \widehat{H}(t)[\sum_{l|t_l<t} \frac{E_l}{R_l(R_l-E_l)}]$.

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, thus biasing the estimation upwards[5].

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 the 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 ($P > \chi^2 = 0.013$).[6]

Figure 2 plots the corresponding rates for termination of the license. 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

[5] One last technical consideration is the treatment of, in the hazard of termination models, 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 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 7585 days since we have no information for these observations beyond that date.

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

firm licensees. The Tarone-Ware test statistic indicates that these survival functions are significantly different ($P > \chi^2 = 0.018$).

Overall, the Kaplan-Meier product limit estimation indicates that for our sample, at virtually any given 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. Although we have not controlled for factors that may influence these survival functions, these estimates suggest that, contrary to some 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 enable 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, campus, 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. We estimate the following hazard function given time t (Blossfeld and Rohwer 1995): $H(t_i) = e^{x_i\beta+\gamma t_i}$. 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.

X includes the variable $START-UP = 1$ if the licensee is a start-up and 0 otherwise plus control variables. $START-UP$ is the main variable of interest in the analysis since we are interested in examining the how the type of licensee (start-up versus established firm) increases or decreases the hazard of an event occurring (commercialization or termination) while controlling for environmental influences. Hypothesis 1 predicts that the hazard rate associated with $START - UP < 1$; that is, the dummy on $START - UP$ will decrease the likelihood of commercial success. Hypothesis 2 predicts that the hazard rate associated with $START - UP < 1$. A firm's status as a start-up will decrease the likelihood of terminating a license to an undeveloped invention.

We condition the analysis on three classes of control variables. First, we include dummies for the year of invention disclosure to capture time-specific effects not assumed by the Gompertz model. Second, we include a dummy variable for each inventor's campus to capture any campus-specific or geographic effects. We recognize inventions made by multiple inventors at different campuses by including a dummy variable for each inventor's campus.

Lastly and most importantly, we control for technology fields. Previous studies of university start-ups utilized either international patent classes (Lowe 2002) or broad technology areas aggregating U.S. patent classifications into five technology classes (Shane 2002) to control for technology field. We depart from this previous literature since we are examining a broader class of inventions than only those for which a patent was issued. We identify the academic departments of primary appointment for each inventor to control for technology field effects. A dummy variable = 1 signifies each inventor's academic department affiliation (e.g., mechanical engineering, physics, or oncology). This approach affords us an attractive comparison. We are effectively comparing the success of start-ups versus established firms in commercializing inventions from the same departments at the same campus.

Table 2 reports the results of regressions for the competing risks of commercialization and termination of inventions licensed by start-ups and established firms. Table 2 displays coefficients with hazard rates in brackets and z-statistics in parentheses. Models 1a and 1b include only a dummy variable for start-ups as a covariate. The hazard rate for commercialization is greater than one (1.400) at a five percent level of significance This results simply reflects our earlier - analysis indicating that start-up firms are more likely to achieve a first-sale from a licensed technology than are established firms before conditioning the analysis on control variables. Similarly, the hazard rate for termination is significantly less than unity (0.697), indicating that start-up firms are less likely to terminate a license than are established firms.

Models 2a and 2b are of more interest. For clarity, we do not report coefficients for the 47 individual academic departments in our analysis or time covariates. In Model 2a, when we control for campus and department, the difference in hazard rates for commercialization by start-ups and established firms becomes non-significant (0.940). This result refutes Hypothesis 1, that start-ups will exhibit a lower likelihood of success than established firms because entrepreneurs overvalue opportunities. That is, start-ups and established firms are equally likely to commercialize inventions discovered in the same university department.

The results in Model 2a also support the literature examining technological characteristics that determine when start-ups develop and commercialize university inventions. The difference in survival rates we estimate non-parametrically (Kaplan-Meier) versus parametrically (Gompertz regressions) is accounted for by differences among technology fields in which start-ups tend to commercialize inventions. Thus, our results are consistent with previous work stating that university start-ups tend to license inventions that are more scientific in nature and in technology fields where the knowledge is more tacit (Lowe 2002, Shane 2002).

In Model 2b, we examine the likelihood of termination with the same control variables as 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 optimistic entrepreneurs will hold projects longer. We term this specific form of cognitive bias to be "denial bias."

An alternative explanation for this observed entrepreneurial persistence lies in the scientific basis for those inventions licensed by start-ups. As mentioned above, we know from previous research that start-ups tend to license inventions that are more scientific or based on "basic research" (Lowe 2002). Thus, while start-ups commercialize in fields that are more scientific or basic research in general– a notion supported by the results of Model 2a– it might be the case that those inventions which are the most basic of the pool of inventions licensed to start-ups and will require the longest periods of time for development.

In addition, Camerer and Lovallo (1999) suggest that an effective test for cognitive bias is to examine areas where the criteria for success are less defined. They argue that overconfidence is most pronounced in such areas because "ambiguity promotes optimism" (Camerer and Lovallo 1999). We propose that Camerer and Lovallo's suggestion is analogous to examining whether cognitive bias persists among inventions that are most scientific in nature since the development path carries greater ambiguity.

To explore these points further, we control for the scientific nature of inventions using the $SCIENCE$ variable proposed by Trajtenberg, Henderson, and Jaffe (1997), and applied to university start-ups by Lowe (2002). $SCIENCE$ measures the level of scientific or basic research underlying an invention based on the proportion of all citations on a patent that are to journal articles (rather than to other patents). Journal articles tend to be closer to basic research than patents in general, and therefore individual patents that heavily cite journal articles will in turn be based on basic research (Trajtenberg, Henderson, and Jaffe 1997). Trajtenberg, Henderson, and Jaffe (1997) test a number of patent-based measures to capture the notion of basic research and find that $SCIENCE$ performs as one of the best measures.

Since the measure is based on patent characteristics, we can only examine the effect of $SCIENCE$ on a subsample of the data, 351 inventions patented and licensed. 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 includes only the $START-UP$ dummy variable and $SCIENCE$; Model 3 is analogous to Model 2a. Model 4 includes the full set of control variables and is analogous to Model 2b.

Surprisingly, we find that $SCIENCE$ does not significantly affect our estimates of the likelihood to terminate a development efforts. The hazard rate is lower on $START-UP$ (0.448 versus 0.595 in regressions without $SCIENCE$), which reflects in part sample bias.

The subsample of 351 inventions introduces bias to our analysis since limiting analysis to patented inventions removes licenses terminated (disproportionately by established firms versus start-ups). Effectively, this decreases the *termination rate* more among established firms and in turn pushes termination rates closer among start-ups and established firms. However, since we are only concerned in these regressions with explaining the difference between the low termination rate among start-ups and a higher rate among established firms, the patent bias actually works against our findings in Models 3 and 4.

The statistically lower termination rate among start-ups after controlling for the level of basic research and after introducing the patent bias significantly strengthens our findings in support of Hypothesis 2. In summary, persistence by start-ups in developing a university invention is not explained by technology area, geographic factors, or the scientific nature of the invention. We propose that entrepreneurs may be in denial about their decreasing chances of success as time continues and commercialization has yet to be reached. Our results are far from conclusive without further research of this kind, but suggest cognitive bias is a strong candidate to explain low termination rates and demands greater attention.

4.3. Economic Returns on Invention

In the final analysis, we focus on only those technologies that are commercialized, excluding terminated and censored observations, to examine whether inventions commercialized by start-ups generate greater or lesser revenues than do those commercialized by established licensees. Recall Hypothesis 3 predicts that if entrepreneurs are overconfident in their analysis of opportunities, then their average returns should be lower versus inventions pursued by established firms. Hypothesis 3 predicts the coefficient on Start-ups will be negative.

To address this question, we follow Shane's (2002) recommendation and employ a tobit analysis of total royalties and fees paid to the university related to a commercialized invention since the distribution of royalties is necessarily truncated on the left at zero. We estimate the natural log of payments to the university as our dependent variable because a few inventions have extreme positive values ("home runs"). However, our sample and analysis differs from Shane (2002) since he only examines returns to *established firm licensees*, rather than comparing royalties generated by start-ups and established firms.

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 inventor's campus.

We find that in the base model (Model 4) licenses to start ups generate greater earnings that inventions licensed to established firms, but these results are weakly significant (significant at the 10% level). The coefficient for start-ups is 1.04 in Model 7 and significantly different from zero at the one percent level. These findings suggest that, measured by economic returns, start-ups actually perform better than do established firms, refuting Hypothesis 3.

In summary, our tests refute Hypotheses 1 and 3, that entrepreneurs appear exhibit cognitive bias in their decisions to found firms to commercialize university inventions. These results are particularly strong in the context of other reasons for entrepreneurial firm failure. New firms are more susceptible than established firms to failure due to random environmental shocks and liability of newness within the organization that are outside the effects of overvaluing market opportunities (Stinchcombe 1965). That is, against the impact of possibly overoptimism and other factors in the firms' liability of newness, entrepreneurial firms continue to perform equal to established firms.

5. Conclusion

The entrepreneurial firm has long played a significant role in the commercialization of university inventions, often pursuing product development after existing firms failed to introduce a product. For example, in 1945 MIT licensed the rights to its Van deGraff patent to High Voltage, Inc., a start-up originated specifically to develop commercial applications for the

MIT technology. High Voltage obtained its license only after General Electric Company had earlier licensed this patent and subsequently failed to commercialize this technology (Etzkowitz 2002). More recently, Calimetrics, a start-up founded by a University of California inventor, was formed to commercialize an optical storage technology originally licensed by a company supplying laboratory equipment to the UC inventors (Lowe 2001). These examples suggest that start-up firms are a viable option for commercialization, despite these firms' limited access to financial capital and complementary assets, factors critical to successful development and introduction of a new technology (Teece 1986).

In this paper we explored commercialization outcomes of university technologies licensed by start-up firms, measured by the time to first sale, time to termination, and level of earnings. Utilizing a novel data set of almost two decades of licensing activity at the University of California, we are able to fill an empirical gap in the literature on entrepreneurial cognitive bias and contribute new theory in the form of "denial bias" by comparing the relative success of start-ups and established firms in commercializing inventions discovered in the same university departments.

Our findings reject the Bold Forecast theory that university entrepreneurs overvalue commercialization opportunities *ex ante* in the decision to found a firm. These results support previous work analyzing the influence of technology characteristics (Lowe 2002) and technology field (Shane 2002, Nerkar and Shane 2003) on the formation of start-ups to develop and commercialize university inventions.

We do find strong evidence for an *ex post* version of the theory: inventors appear to hold on to technologies without commercial success longer than do established firms. These results suggest that entrepreneurs may be "in denial" about their diminishing prospects of successful commercialization. We propose that this notion of "denial bias" offers fertile ground for future research in characterizing the reasons for some inventions to require considerable periods of development time. Specifically, further research is recommended on separating potential denial bias from inventions that are sufficiently complex to warrant long development cycles.

This apparent denial bias may be supported by a combination of human (cognitive bias) as well as institutional factors, in particular the rise of public funding programs for start-ups (Lerner 1999). It is not uncommon for university ventures to be funded by government agencies (Lowe 2001) or for universities to lower the cost of licensing for entrepreneurs through equity arrangements (Feldman, Feller, Bercovitz and Burton 2002). DiGregorio and Shane found that not all universities seem equally capable in identifying new firms as potential licensees (DiGregorio and Shane 2003). Campuses with strong research reputations and universities with favorable policies towards inventor reimbursement and equity investment encouraged greater new firm formation.

Such policies exert less direct monitoring than private funders, such as venture capitalists, since the agencies are primarily focused on funding early stage technologies. The normative implications of our results are that universities and public funding agencies may need greater oversight in monitoring university inventions that have yet to reach commercial status in order to separate lagging technologies from complex development projects.

University start-ups offered a particular robust environment to examine the relative performance of start-ups versus established firms in commercializing inventions. This research recommends future work of this nature outside the university environment to build more generalizable conclusions. Comparing success rates of corporate spin-offs versus their parents in development projects is an obvious extension. Our findings also show the need for more fine-grained analysis of success in individual projects rather than overall firm failure rates, which has been cited as rough evidence for cognitive bias. Our work is consistent with the believe that well established firms are sufficiently large to absorb more failures without declaring bankruptcy, while the organizational life span of a small, new firm is sensitive to the outcome of a single project. Comparing firm survival rates to examine entrepreneurial cognitive bias appears, at least in the university setting, to be masking the true story.

Finally, a stated goal of most university technology transfer professionals is to facilitate development of new products based on university research. Our evidence suggests that the active pursuit of start-up licensing is a worthwhile endeavor. University entrepreneurs should remember and relish in their successes, but it is at least as important to recognize and forget their failures.

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

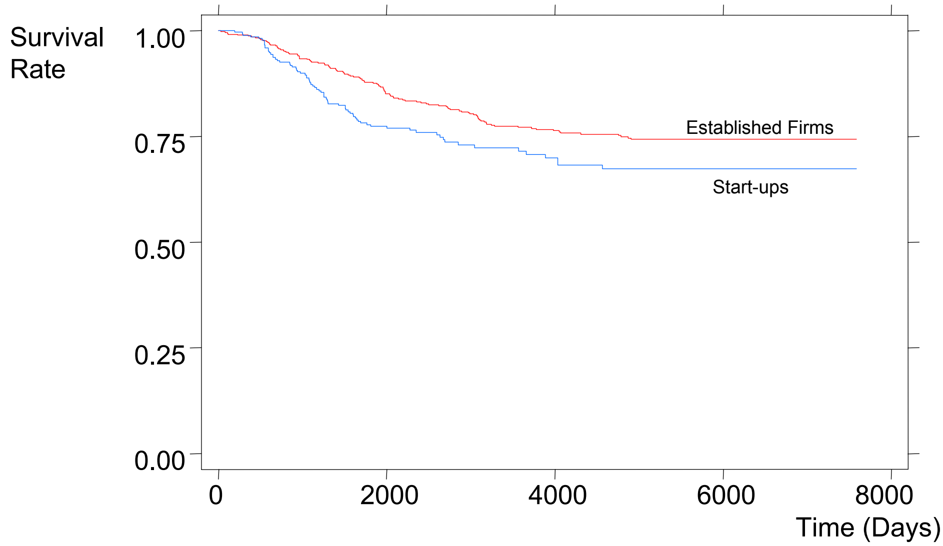

Figure 2. Kaplan-Meier Survival Estimates for Hazard of Project Termination

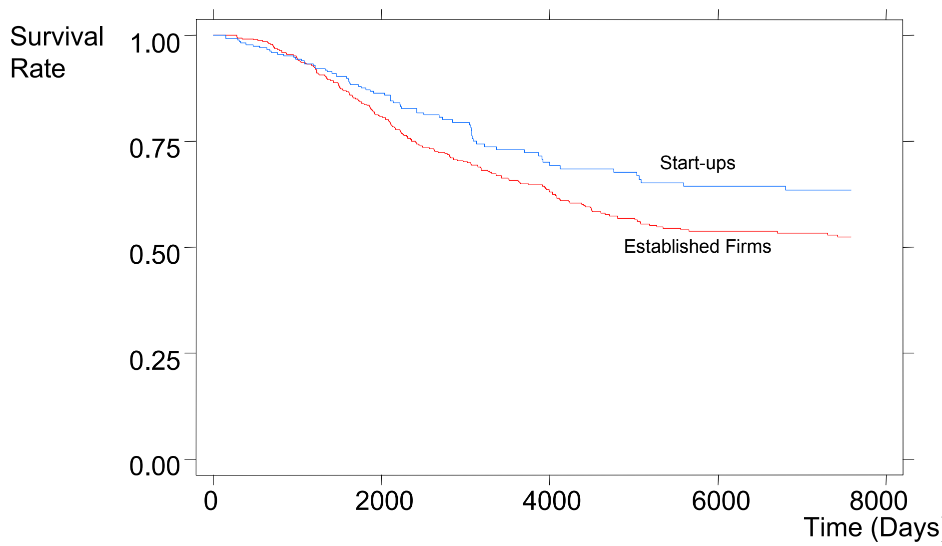

Table 1. Survival outcomes by licensee type (start-up vs. established firm)

		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%

Table 2. Competing Risk Models of Commercialization and Termination
Coefficients reported with hazard rates in brackets and absolute value of z-stat in paren.

	(1a) Commercialized	(1b) Terminated	(2a) Commercialized	(2b) Terminated
Start-up	0.336	-0.361	0.126	-0.520
	[1.400]	[0.696]	[1.134]	[0.595]
	(2.24)**	(2.62)***	(0.65)	(3.12)***
Berkeley			-0.881	0.200
			[0.414]	[1.221]
			(1.43)	(0.37)
Davis			-0.602	0.394
			[0.548]	[1.482]
			(0.97)	(0.73)
Irvine			-0.377	-0.461
			[0.685]	[0.630]
			(0.61)	(0.77)
Los Angeles			-1.433	0.820
			[0.239]	[2.271]
			(2.52)**	(1.85)*
Riverside			-0.967	0.550
			[0.380]	[1.732]
			(1.10)	(0.69)
Santa Barbara			-0.870	0.097
			[0.419]	[1.101]
			(1.13)	(0.15)
San Diego			-1.287	0.381
			[0.277]	[1.464]
			(2.42)**	(0.87)
San Francisco			-2.058	0.733
			[0.127]	[2.082]
			(3.86)***	(1.71)*
Year Dummies			Yes	Yes
Inventor Department			Yes	Yes
Constant	-9.064	-8.962	-8.033	-8.946
	(71.10)***	(85.26)***	(9.45)***	(14.96)***
χ^2 test statistic	4.90**	7.23***	177.56***	186.47***

Observations = 734
(1) significant at 10%; ** significant at 5%; *** significant at 1%*
(2) χ^2 test statistic refers to test that all coefficients are jointly zero

Table 3. Survival Analysis of Termination

Sample only includes 351 inventions between 1986-1995 that were patented.
Coefficients reported with hazard rates in brackets and absolute value of z-statistic in parentheses.

	(3)	(4)
Start-up	-0.498	-0.804
	[0.608]	[0.448]
	(2.36)**	(2.92)***
Science	0.259	0.397
	[1.295]	[1.488]
	(1.05)	(1.12)
Campus		Yes
Year Dummies		Yes
Inventor Department		Yes
Constant	-9.223	-9.073
	(44.68)***	(10.85)***
χ^2 test statistic	6.44**	142.45***

Observations = 351
*(1) * significant at 10%; ** significant at 5%; *** significant at 1%*
(2) χ^2 test statistic refers to test that all coefficients are jointly zero

Table 4. Tobit regressions of natural log of university earnings (Absolute value of t-statistics in parentheses).

	(5)	(6)	(7)
Startup	0.552	0.893	1.04
	(1.71)*	(2.65)***	(3.12)***
Berkeley			-0.21
			(0.19)
Davis			-0.163
			(0.15)
Irvine			-1.229
			(1.11)
Los Angeles			-0.922
			(0.93)
Riverside			3.05
			(1.77)*
Santa Barbara			-0.338
			(0.25)
San Diego			-1.472
			(1.56)
San Francisco			-1.379
			(1.61)
Inventor's Department		*Included in models 8 and 9*	
Year Dummies		*Included in models 7-9, see notes below*	
Constant	14.174	14.884	17.083
	(12.52)***	(12.32)***	(11.57)***
Pseudo-R^2	0.0683	0.1643	0.1837
χ^2 test statistic	57.55***	138.49***	154.81***

Observations: 188

(1) significant at 10%; ** significant at 5%; *** significant at 1%*

(2) χ^2 test statistic refers to test that all coefficients are jointly zero