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The performance of university spin-offs: an exploratory analysis using venture capital data

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Abstract University spin-offs are defined as firms founded by university employees. Using a large database on venture-backed start-up companies, I describe the characteristics of university spin-offs and investigate whether they perform differently than other firms. I find that venture-backed university spin-offs are concentrated in the biotechnology and information technology industries. Moreover, a spin-off tends to stay close to the university, suggesting that technology transfer through spin-offs is largely a local phenomenon. Multivariate regression analyses show that university spin-offs have a higher survival rate but are not significantly different from other start-ups in terms of the amount of venture capital raised, the probability of completing an initial public offering (IPO), the probability of making a profit, or the size of employment.

Keywords University spin-off · Academic entrepreneur · Technology transfer · Venture capital · Entrepreneurship

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1 Introduction

The focus of this study is venture-backed university spin-offs. I define university spin-offs as companies founded by university employees and refer to their founders as academic entrepreneurs. Using a large venture capital database, I characterize venture-backed

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university spin-offs and academic entrepreneurs along various dimensions and examine whether university spin-offs perform better than other venture-backed firms.

University spin-offs are by no means a new phenomenon, especially in the biotechnology industry (Kenney 1986a, b). Leading biotech firms such as Genentech, Amgen, Biogen, and Chiron were all founded or cofounded by university professors. The information technology industries, although better known for college-dropout entrepreneurs such as Bill Gates, Steve Jobs, and Michael Dell, also provide many examples of academic entrepreneurs. Silicon Valley's most famous serial entrepreneur, Jim Clark—the founder of Silicon Graphics, Netscape, Healtheon, myCFO, and Shutterfly.com—started his career as a professor at UC Santa Cruz and later Stanford University. Lycos (one of the leading Internet search engines), Akamai (the global leader in distributed computing solutions and services), and Cisco Systems also trace their origins to university employees.[1]

University spin-offs are studied primarily by researchers who seek to understand the phenomenon of technology transfer from university to industry (Etzkowitz 2002; Feldman 1994; Feldman and Desrochers 2003; Roberts 1991; Shane 2004). These scholars have recognized that the creation and dissemination of knowledge at universities have increasingly become an important driving force for technological innovation and economic growth. It is often argued that a great deal of knowledge created at universities is tacit and uncodifiable and that the dissemination of such knowledge relies on direct interpersonal contact. Professional mobility, therefore, is considered a critical element in transmitting knowledge, and the movement of university employees from academia to industry constitutes an important channel for technology transfer (Zucker et al. 2002). Indeed, almost all existing studies of university spin-offs were conducted in this context (see, e.g., Chiesa and Piccaluga 2000; McQueen and Wallmark 1982; Rogers 1986; Samson and Gurdon 1993; Smilor et al. 1990; Steffensen et al. 2000; Wright et al. 2004).

The goal of this paper is to contribute to the literature on technology transfer. My research question, however, draws its motivation more directly from a separate literature on spin-offs from companies, which focuses on the linkage between spin-offs and their parent companies. Spin-offs are thought to be influenced by parent companies. For example, spin-offs of an existing company often enter the same industry as competitors or partners of the parent company. More importantly, the knowledge and experience that spin-off founders gained at the parent organization may have an effect on the performance of their companies. As Klepper and Sleeper (2005) argue, the knowledge that spin-off companies inherit from their parents not only shapes their nature at birth, but also affects their organizational behavior and business strategy. Recent studies on spin-offs from existing companies are all motivated by this argument (see, e.g., Agarwal et al. 2004; Gompers et al. 2005; Klepper 2001; Klepper and Sleeper 2005). However, researchers have rarely examined university spin-offs from this perspective.

Given that academic entrepreneurs were actively involved in knowledge creation and dissemination at universities, one would expect that their academic affiliation would influence the performance of their business ventures. For example, academic entrepreneurs may start businesses in order to commercialize some advanced technology discovered in universities. Such technology could give university spin-offs a competitive edge over other firms and thus an enhanced chance of success. Also, university spin-offs are often founded by distinguished scientists. These founders' academic reputation may help their businesses

[1] It is well known that the popular Internet search engines Yahoo! and Google both grew out of Stanford. However, they were founded by students rather than university employees and thus, by my definition, are not considered university spin-offs in this paper.

in many ways, including by attracting equity investments. Therefore, I hypothesize that university spin-offs perform better than other firms. Using a large sample of venture-backed companies, I examine whether this hypothesis holds true.

A paucity of data has always constrained research on university spin-offs. As a result, previous researchers tend to focus on a small number of universities and rely on case studies or small-scale survey data. McQueen and Wallmark (1982) study spin-off companies from the Chalmers University of Technology in Sweden. Smilor et al. (1990) examine technology start-ups from the University of Texas at Austin. Using personal interviews, Steffensen et al. (2000) analyze six spin-off companies from the University of New Mexico. Kenney and Goe (2004) use mail survey and Internet data to compare "professorial entrepreneurship" at UC Berkeley and Stanford. Wright et al. (2004) compare two university spin-offs with two university-industry joint ventures based on an in-depth telephone and face-to-face interviews. These small-sample studies, although each revealing a useful piece of information, are unable to provide a comprehensive understanding of university spin-offs. As a result, the current state of knowledge on university spin-offs is highly fragmented. It is, therefore, important to construct large data samples for research in this area.[2]

The data constraint also results in an inconsistency among existing studies of university spin-offs. Depending on the data at hand, researchers often invoke different definitions of academic entrepreneurship and university spin-offs.[3] Klofsten and Jones-Evans (2000) use a very broad definition of academic entrepreneurship that covers not only new firm formation but also consulting and patent-seeking activities of academics. In Stuart and Ding (2006), an academic entrepreneur may not be a firm founder but simply an academic scientist who serves on the scientific advisory board of a start-up. Druilhe and Garnsey (2004) define university spin-offs as companies founded by academics or students who are still members of or have just quit a university. In several studies, Shane and his coauthors investigate "university spin-offs" as start-ups exploiting university inventions but not necessarily founded by university employees (Shane and Stuart 2002; Di Gregorio and Shane 2003; Nerkar and Shane 2003; Shane 2004).[4] This last definition of university spin-offs appears to be the most widely used among researchers (see, e.g., Clarysse et al. 2007; Link and Scott 2005; Lockett et al. 2005; Lockett and Wright 2005; Lowe and Ziedonis 2006; O'Shea et al. 2005; Siegel et al. 2007; Wright et al. 2006; Zahra et al. 2007). These studies, although closely related to my work, do not examine the exact type of businesses and entrepreneurs as I do in this study.

In this paper, I employ a comprehensive venture capital database to study the performance of university spin-offs. This database tracks venture-backed start-ups in the United States and thus contains detailed firm-level information. In addition, it has biographical information about a large number of start-up founders, which can be used to identify whether a founder has ever worked for a university. I study what areas of specialty venture-backed academic entrepreneurs tend to come from, what industries their companies tend to enter, and whether these spin-offs are located in the same state as the universities. More importantly, I examine whether venture-backed university spin-offs perform better than

[2] Lowe and Gonzalez-Brambila (2007) is perhaps the only study analyzing a relatively large database that contains 150 academic entrepreneurs in 15 academic institutions. They refer to academic firm founders as "faculty entrepreneurs," and their study focuses on such entrepreneurs rather than their companies.

[3] See Pirnay et al. (2003) for a typology of university spin-offs.

[4] Data on companies founded to exploit MIT intellectual property during 1980–1996 show that a university inventor was the lead entrepreneur in about only one-third of the companies (Shane 2004, pp 6–7).

other start-ups in terms of the amount of VC raised, the probability of completing an initial public offering (IPO), the chance of making a profit, and the size of employment.

The main contribution of this paper is compiling and analyzing a substantially larger data sample to present a broad range of evidence on university spin-offs that was previously unavailable. The larger sample permits a richer understanding of venture-backed university spin-offs, especially their performance compared to other venture-backed firms. In spite of this improvement upon existing literature, this study is not without its limitations. In particular, the data sample is constructed from a database that was not originally designed for the purpose of studying university spin-offs. As a result, the sample covers venture-backed firms only, not representative of the population of all university spin-offs. In fact, it may not even be a random sample of venture-backed university spin-offs, because firms with founder information missing have to be excluded from my analysis. Therefore, the empirical results in this study are subject to sample selection biases. Furthermore, it is impossible to correct for such potential biases due to a lack of information. For these reasons, the analysis in this study is exploratory in nature and the empirical results are mostly suggestive rather than conclusive. Nonetheless, I hope that this study will help researchers as well as practitioners better understand the phenomenon of university spin-offs and stimulate further research along this line.

In the following section, I describe the data used in this study. Section 3 presents some descriptive statistics, including the specialty, industry, and business location of venture-backed academic entrepreneurs. Section 4 presents multivariate analyses of start-up performance, focusing on whether university spin-offs are significantly different from other venture-backed firms. Section 5 offers some concluding remarks.

2 Data

The data used in this paper were acquired from VentureOne, a leading VC research company based in San Francisco. Founded in 1987, VentureOne tracks equity investment in the United States. It collects data by surveying VC firms for recent funding activities and portfolio updates, gathering information through direct contacts at venture-backed companies, and investigating various secondary resources such as company press releases and IPO prospectuses (VentureOne 2001). VentureOne tries to capture all of the venture-backed companies in the United States and their early-stage financing events.[5]

For each VC deal, VentureOne keeps a record of its size, stage of financing, closing date, VC firms involved, and detailed information about the firm that received the money, including its address, start year, industry, etc. VentureOne continues to track the venture-backed company, updating the information about its employment, business status, and ownership status until the VC support concludes as a result of a bankruptcy of the venture-backed company, an IPO, or a merger and acquisition (M&A) that allows venture capitalists to cash out. Although VentureOne's database is maintained for commercial

[5] VentureOne defines a venture capital firm as "a professional, institutional venture capital limited partnership that generally manages over $20 million in assets and invests in privately held companies" (VentureOne 2000). Once a company receives some investment from venture capital firms, it becomes a "venture-backed company" and enters the VentureOne database. VentureOne then tracks the company's financing from all sources, including bank loans and IPO. While I do not count bank loans or money raised through an IPO as venture capital, I do include equity investment made by non-VC corporations or "angel investors" as venture capital in my calculations.

purposes, many academic scholars have used it for empirical research.[6] Comparing VC databases with actual VC financing contracts, Kaplan et al. (2002) find that the VentureOne data are generally more reliable, more complete, and less biased than the Venture Economics data, the only other major source of VC data.

The data used in this study were extracted from VentureOne's database at the end of 2001, which covers VC deals completed from the first quarter of 1992 through the fourth quarter of 2001. It includes 22,479 rounds of VC financing involving 11,029 venture-backed firms. Among these firms, 83.5% were founded in or after 1990.[7]

VentureOne also provided a separate data set containing brief biographical information about the founders of venture-backed firms. These data describe the founder's working experiences, which, in most cases, not only specifies the companies or institutions a founder worked for but also includes the position he or she held. However, the founder data are incomplete: Founder information is available for 6,359 of the 11,029 venture-backed firms. Many firms are cofounded by more than one individual, yielding a total of 10,530 individual founders.

Because of the way VentureOne manages its database, the availability of founder information is not entirely random. A firm enters VentureOne's database once it receives equity investment from a venture capital firm. VentureOne regularly updates the information about the venture-backed firm until it ceases operation, is acquired, or goes public.[8] VentureOne thus follows some firms longer than others, and they are more likely to capture a firm's founder information if the firm has been followed longer. VentureOne also appears to be more likely to have founder information for firms founded in the late 1990s, possibly because these firms tend to reveal more company and founder information on their websites.

Table 1 compares firms whose founder information is available with those whose founder information is missing. Clearly, these two sub-samples of the VentureOne data differ along many dimensions. Firms with founder information tend to be founded in the later sample period. For example, 37.5% of them were founded after 1997, and 20.8% of them were founded before 1994. In contrast, among firms with founder information missing, only 17.8% were founded after 1997 and 59.1% were founded before 1994. Firms with founder information tend to be privately held and are less likely to be out of business, to have been acquired, or to have completed an IPO, which is consistent with the fact that they are younger. In addition, these two samples are also different in terms of industry composition. For example, firms with founder information available are much more likely to be in the consumer/business services and information services industries, but much less likely to be in the electronics, healthcare, and medical devices industries. The Pearson's χ^2 tests reject the hypothesis that the distributions of the two samples (over founding year, ownership status, and industry) arise from random sampling.[9]

[6] Recent empirical work using the VentureOne data includes Gompers and Lerner (2000), Cochrane (2005), Gompers et al. (2005), and Zhang (2006, 2007).

[7] For a more detailed description of the VentureOne data, see Zhang (2007).

[8] For VentureOne's research methodology, see http://www.ventureone.com/ii/research.html (accessed on December 23, 2005).

[9] As I will argue below, it is more appropriate to drop all the firms founded before 1990 in the regression analyses. So the Pearson's χ^2 tests are also conducted for the two subsamples excluding firms founded before 1990. The hypothesis that these two subsamples arise from random sampling is again rejected.

Table 1 Comparison of firms with founder information available to those with founder information missing

	Venture-backed firms with founder information available	Venture-backed firms with founder information missing
Panel A: founding date		
Founded before 1994	20.81	59.06
Founded during 1994–1997	41.70	23.18
Founded during 1998–2001	37.49	17.76
Pearson's $\chi^2(2) = 4.3e + 03$; P-value $= 0.000$		
Panel B: ownership status		
Went out of business	17.17	32.27
Merged/acquired	9.48	11.13
Privately held	58.68	34.31
Completed an IPO	14.67	22.28
Pearson's $\chi^2(3) = 1.8e + 03$; P-value=0.000		
Panel C: distribution over industries		
Advance/special material and chemical	0.44	1.08
Agriculture	0.12	0.50
Biopharmaceutical	6.36	8.87
Communication	13.42	13.10
Consumer/business products	1.05	3.51
Consumer/business services	20.02	12.47
Electronics	3.31	7.90
Energy	0.18	0.40
Healthcare	1.91	5.29
Information services	10.49	5.52
Medical devices	4.81	9.13
Medical information services	2.95	3.41
Retailing	3.27	4.22
Semiconductor	4.31	3.33
Software	27.21	19.77
Other	0.16	1.53
Pearson's $\chi^2(15) = 1.9e + 03$; P-value $= 0.000$		

The unit of observation is the firm. In each panel, column percentages are shown in the cells. There are 6,359 venture-backed firms with founder information available and 4,670 firms with founder information missing. Pearson's χ^2 tests are conducted to test the null hypothesis that the frequencies arise from random sampling. The P-value indicates the probability of obtaining a result more extreme than the test statistic under the null hypothesis

For the purpose of this study, I will focus only on firms with founder information available and drop all other firms from my empirical analysis. Given the difference between the two samples shown in Table 1, the sample being analyzed is unlikely to be representative of the whole population of venture-backed firms. This implies that my regression results are subject to potential sample selection biases and they should be interpreted with caution.[10]

Since VentureOne did not code founders' biographical information, I first construct a variable to indicate whether a founder previously worked for a university or college. Whenever an academic entrepreneur is identified, I assign values to a set of variables including the name of the academic institution, the founder's academic position, the founder's specialty (if identifiable), and the state where the institution is located.[11] For a small group of founders who have worked at more than one academic institution, I count the latest academic position only.

The firm data and the founder data share a common variable, "EntityID," by which I can match a firm with its founder if founder information is available. With these data, I can calculate simple descriptive statistics to characterize university spin-offs as well as academic entrepreneurs along many dimensions.

It is worth noting that even in Silicon Valley, the world's largest VC investment center, only a small fraction of start-ups receives VC financing (Zhang 2003). By focusing on venture-backed firms, I am excluding a large proportion of the industry. However, venture-backed start-ups often possess the greatest growth potential and may have a much greater effect on the whole economy than their share implies. In addition, the richness of the data is unparalleled and the size of the sample is much larger than those analyzed by existing studies. This provides an opportunity to examine a much broader range of evidence and gain a better understanding of the phenomenon of academic entrepreneurship.

3 Academic entrepreneurs and university spin-offs: descriptive statistics

Among the 10,530 venture-backed firm founders in the VentureOne data, 903 have been affiliated with academic institutions, accounting for 8.6% of the total. These 903 individuals founded or co-founded 704 venture-backed firms; 35 of them have more than one firm in the data. This section describes the specialties and academic affiliations of academic entrepreneurs and summarizes industry and geographic distributions of the university spin-offs that they founded.[12]

[10] Gompers et al. (2005), who study spin-offs from public companies using data extracted from the same VentureOne database, try to supplement the data by searching for the missing founder information using alternative sources such as Google and Lexis–Nexis. However, I cannot do the same. When I obtained the data from VentureOne, the company was very much concerned about researchers' practice of tracking down the founders. So they replaced all company names and founder names with identification numbers. This makes it impossible for me to complement the founder data using alternative sources like Gompers et al. did. Note that Gompers et al. search alternative data sources only to construct a more complete sample. It is not meant to and cannot solve the sample selection problem. Because information about successful entrepreneurs tends to be more easily available, their searches have the same sort of sample selection problem as the original VentureOne database does.

[11] An academic entrepreneur's specialty is not always identifiable using the VentureOne data. For example, a firm founder's biographical sketch might read like this: "professor, Stanford University." In this case, I left the "specialty" field blank. In other cases, more information is available, such as "professor, Department of Computer Science, Stanford University," or simply "professor of physics, Stanford University," which enables me to identify this person's specialty.

[12] To a great extent, what I choose to present in this section is determined by the availability of data. There are many other characteristics of academic entrepreneurs and their firms that would be interesting to explore. For example, do academic entrepreneurs enter the industry that is most closely related to their academic field? Do young professors have a higher tendency to become academic entrepreneurs than older ones? The VentureOne data are not suitable for answering these questions because the information is either incomplete or entirely unavailable.

3.1 Entrepreneurs' positions at academic institutions

Table 2 summarizes the highest (most recent) positions these academic entrepreneurs held at universities. Note that these could reflect either current or former posts. The VentureOne data do not indicate whether a firm founder has given up his or her position in a university. Anecdotal evidence suggests that professors could retain their academic positions when they start firms;[13] yet non-tenure track employees may have to resign their university employment if they choose to become entrepreneurs.

As Table 2 shows, nearly two-thirds of the entrepreneurs from universities are professors. Most of the individuals in this group are self-identified as professors. A few of them are "dean" or "chairman" of some academic departments, and so are undoubtedly also professors. I categorize these individuals into the "professor" group instead of the "executive" group.

The second largest group (close to 16% of the total) is comprised of research scientists at universities. These individuals usually identified themselves as researchers at university laboratories. It is likely that they did not hold tenure track positions and it is impossible to tell from the VentureOne data whether they also taught at the universities.

The third group consists of "directors." This group may overlap with some of the other groups. For example, the director of a research lab at MIT is almost surely a professor or a research scientist; on the other hand, the director of the department of continuing education in a university could be an executive. Rather than using subjective judgment to assign these people to other groups, I categorized them into a separate group.

The professor and research scientist groups constitute 78.2% of the total number of entrepreneurs who ever worked for universities. If combined with the director group, the proportion rises to 86.1%. This implies that around 80% of the academic entrepreneurs held research positions at academic institutions. Most likely, they started new businesses to commercialize their research findings.

The executive position and the lecturer/instructor position are also self-identified, with the latter likely to be non-tenure track temporary teaching jobs. And finally, all other job positions are lumped together in the "other group," which includes technicians, programmers, and other staff members in various academic or administrative departments at universities.[14]

Among the 903 academic entrepreneurs, 669 have identifiable specialties. Table 3 shows the distribution of these individuals by specialty. Most of the academic entrepreneurs have an engineering or science background, which is not surprising given that VC investment is overwhelmingly concentrated in high-tech industries. More than 45% of academic entrepreneurs (304 out of 669) specialize in engineering; 186 of them have a background in computer science or electrical engineering. Another 44% of academic

[13] For example, Herbert Boyer, cofounder of Genentech in 1976, remained a professor of biochemistry at UCSF until 1991; Richard Newton helped found a number of design technology companies including Cadence, Synopsys, and Simplex Solutions but never left UC Berkeley; Phillip Sharp, a cofounder of Biogen in 1978, is still a professor at MIT.

[14] There are 23 entrepreneurs whose biographical information contains university names, but they were listed as "research assistants," "Ph.D. students," or "post-doc fellows" and did not hold formal job positions at universities. I excluded these founders from the group of academic entrepreneurs shown in Table 2. One could argue that these individuals should also be counted as academic entrepreneurs. However, it is very possible that many of the founders do not consider these as important job experiences and therefore do not include them in their biographical sketches. For example, there are simply too few post-docs in the sample, which seems to be a result of underreporting. Thus, leaving them out is better than including them as academic entrepreneurs because the latter definition could lead to more serious measurement errors.

Table 2 Highest positions that entrepreneurs ever held in academic institutions

Position	Number of Individuals	Percentage of total (%)
Assi./Asso./Full Professor	563	62.35
Research scientist	143	15.84
Director	71	7.86
Executive	69	7.64
Lecturer/Instructor	17	1.88
Other	40	4.43
Total	903	100

Table 3 Distribution of entrepreneurs by specialty

Academic discipline	Number of entrepreneurs	Percentage of Total (%)
Engineering	304	45.44
Medical sciences	175	26.16
Bioscience	96	14.35
Business	29	4.33
Chemistry	23	3.44
Other	42	6.28
Total	669[a]	100

[a] Specialty is unidentifiable for 234 of the 903 academic entrepreneurs

entrepreneurs specialize in medical sciences, biological sciences, or chemistry. Business professors form the largest non-scientist/engineer group among academic entrepreneurs. The “other” group represents a wide range of specialties, including architecture, economics, physics, psychology, and statistics. Social sciences and humanities are extremely underrepresented, with fewer than ten of the academic entrepreneurs coming from such backgrounds.

3.2 Distribution across industries

Table 4 presents the distribution of all venture-backed companies and venture-backed university spin-offs across industries. I use the industry classification provided by VentureOne, which has assigned each company to one of 16 different industry segments.

Overall, there are 10,530 entrepreneurs in my study sample. These entrepreneurs are associated with only 6,359 firms, because it is common to have two or more entrepreneurs cofound a firm. For the same reason, the 903 academic entrepreneurs in the sample founded only 704 university spin-offs. Whereas the 903 academic entrepreneurs constitute 8.6% of the total number of entrepreneurs, the 704 university spin-offs account for 11.1% of the total number of companies. The percentage of university spin-offs varies substantially across industries. While only 4.8% of the firms in the consumer/business services industry are university spin-offs, more than 50% of the biopharmaceutical companies originate from universities.

The biopharmaceutical industry has the largest number of university spin-offs, followed by the software industry as a close second. Together, these two industries account for more than half of the 704 university spin-offs. In terms of the total number of companies, the

Table 4 Distribution of university spin-offs by industry

Industry[a]	Total number of start-ups in sample	Number of university spin-offs	University start-ups as % of industry (row) total
Advance/special material and chemical	30	8	26.67
Agriculture	5	0	0
Biopharmaceutical	355	182	51.27
Communication	801	72	8.99
Consumer/business products	71	7	9.86
Consumer/business services	1,426	69	4.84
Electronics	194	20	10.31
Energy	10	2	20.00
Healthcare	106	7	6.60
Information services	696	37	5.32
Medical devices	252	47	18.65
Medical information services	187	35	18.72
Retailing	182	2	1.10
Semiconductor	264	36	13.64
Software	1,768	179	10.12
Other	12	1	8.33
Total	6,359	704	11.07

[a] This follows VentureOne's industry classification that divides start-ups into 16 different industry segments

software industry is almost 5 times as large as the biopharmaceutical industry (1,768 vs. 355). However, the biopharmaceutical industry has more university spin-offs than the software industry (182 vs. 179). In fact, the proportion of university spin-offs in the software industry is slightly below average.

The fact that the biopharmaceutical industry and the software industry have the most university spin-offs is not surprising. It is well known that venture capitalists tend to invest in high-technology start-ups with great potential for rapid growth, which fit the characteristics of both industries. It is also well-known that academic scientists and their universities, stimulated by the Bayh–Dole act and enabled by the large amount of funding from government agencies such as the National Science Foundation, the National Institute of Health, and the Department of Defense, have created and own a large amount of intellectual property that is potentially commercializable. In addition, it is now often a research university's explicit intention to encourage and support faculty members and other employees to commercialize their inventions. Universities such as MIT, Stanford, and Georgia Tech even created research parks and incubators to facilitate academic entrepreneurship in biotechnology and software development. Thus one would expect to see many university spin-offs in these industries.

Nonetheless, the high proportion of university spin-offs in the biopharmaceutical industry is still very striking: 51.3% of the venture-backed companies in this industry are founded by university employees. Other major industries (with more than 50 companies in the sample) with a particularly high share of university spin-offs include the medical information service (18.7%) and medical device (18.7%) industries. But both are far from comparable to the biotech industry in terms of the prevalence of university spin-offs.

University spin-offs constitute such a large proportion of venture-backed start-ups in the biopharmaceutical industry that it clearly calls for further explanation. A few possible reasons may account for this phenomenon.

(1) Marketability of technology

In general, whether an inventor benefits from an invention depends on whether it is easily marketable. If there is already a strong demand for the technology, as in the case of Nobel's dynamite, the inventor will immediately see the economic value and try to capture it. On the other hand, if there is no apparent market value, as in the cases of the personal computer and the Internet, the inventor may miss the chance to reap the economic benefit. In such situations, it usually takes one or more entrepreneurs to bring the technology to the market, and it is the entrepreneurs rather than the inventor who are financially rewarded. For example, personal computers found few buyers when the technology first became available. IBM, Hewlett-Packard, and DEC all missed the chance to be the first to mass-market personal computers, although they were in a better position than anyone else. It was Steve Jobs, not the inventor of the technology, that founded Apple Computer and established the enormous PC market.

On the other hand, the application of biotech and medical research in the healthcare industry has long been well known. Biotechnology does not need to create its own demand; it helps serve the multibillion dollar market that already exists for medicinal drugs. Because this market awaits technological breakthroughs, the inventors themselves (often professors) will see the economic value of biotechnology and seek to realize it.[15]

(2) Asymmetric information and signaling

Most start-ups in the biotech industry remain unprofitable over a long horizon. It usually takes many years to develop a viable biotech product; and then many of these products have to proceed through a lengthy approval process at the Food and Drug Administration (FDA). The start-up can fail at any stage. Thus, investment in biotech is highly risky. Related to this risk is an asymmetric information problem between entrepreneurs and investors: Entrepreneurs know more than investors about the risk involved in the proposed project, and it is extremely difficult for investors to acquire the knowledge to fully evaluate a biotech start-up's business plan.[16] This informational asymmetry requires venture capitalists to make investment decisions based partially on their faith in the entrepreneurs. Facing this problem, entrepreneurs want to send signals to investors revealing the long-term value of their ideas. Naturally, a record of outstanding work in hard science is the most convincing evidence that the entrepreneur knows the true value of the proposed idea and has the required knowledge to implement it. To venture capitalists, the academic background of a biotech firm founder is not only a good signal of the entrepreneur's ability but also a selling point when they need to cash out. Venture capitalists often want to cash out through an IPO or acquisition long before a biotech start-up shows any profit. But how could they convince ordinary investors or a potential acquirer that a currently unprofitable start-up is worth something? Clearly, a scientist founder is a very valuable selling point. If this is indeed an issue that venture capitalists consider when evaluating biotech start-up

[15] Although the existing market demand for more effective drugs is obvious, biotechnology may have some other applications that are unknown today. If some of these applications are carried out in the future, it is likely that non-academic entrepreneurs, rather than university professors, will make it happen.

[16] See, for example, Leland and Pyle (1977) for a formal discussion of the informational asymmetries between entrepreneurs and investors.

proposals, academic scientists (most of whom are university professors) should have a better chance to pass the screening process than other entrepreneurs.

(3) Diffusion of technology

Biotechnology is sophisticated, not easily codifiable, and well protected by patent law. All of these features make the diffusion of biotechnology relatively slow. Therefore, for a long time after a technology is developed, only the chief scientist (very likely a university researcher) and others involved in making the technological breakthrough are in the position to commercialize it. This is in sharp contrast to the situation in other technology industries. For example, during the Internet boom, the core technology of many dot-coms, such as Amazon.com and eBay, was no more than an innovation in usability. Such innovations can be quickly understood and imitated by many people and therefore do not need academic scientists to bring them to market. This is not the case with complex biotechnologies.

3.3 University location versus spin-off location

An important question regarding university spin-offs is whether they are located close to their parent universities. In other words, to what extent is knowledge transfer through academic entrepreneurship a local phenomenon? This question concerns not only researchers who are interested in the process of technology transfer, but also state and local policymakers who want to know the benefits of research institutions to local economies.

Using the merged firm and founder data, I describe the distribution of university spin-offs by both parent-university and business locations (Table 5). Out of the 704 university spin-offs, 45 are traced to academics at universities in foreign countries such as Britain, Canada, Germany, and Israel.[17] The rest (659 spin-offs) are from U.S. universities, among which 449 or 68.1% are located in the same state as the university. Similarly, 67.7% of academic entrepreneurs founded their businesses in their home state. That is, less than one-third of academic entrepreneurs moved to other states.

From a state's point of view, some academic entrepreneurs leave the state and others arrive. Table 5 shows the net flow of university spin-offs at the state level. California is clearly the "winner." In the whole sample, California universities generated 195 venture-backed spin-offs; yet 290 spin-offs were located in California. Whereas 18 spin-offs from California universities left the state, 113 spin-offs located in California can be traced to universities in other states, resulting in a net gain of 95 university spin-offs for California. This is not surprising given that the data set covers the VC deals completed between 1992 and 2001, during which time the Internet revolution was the primary driver of VC investment and California was the main destination of this "digital rush." Besides California, other significant winners include Texas (with a net flow of +6), Washington (+6), Virginia (+5), Arizona (+5), and Oregon (+5). Obviously, all of these winning states are nowhere near comparable to California.

Since the data only include venture-backed firms, one may expect that entrepreneurs chase money and that a state with plentiful VC investment is guaranteed a net gain of university spin-offs. This is not the case. Massachusetts is number two in terms of total VC investment, and its academic institutions generated 132 spin-offs. However, compared to California, Massachusetts has a fairly low retention rate. About 38, or 28.8% of the 132

[17] VentureOne data include foreign researchers who founded firms in the United States but do not include U.S. researchers who started businesses overseas. Thus it is impossible to measure the net flow of academic entrepreneurs between the United States and the rest of the world using the VentureOne data.

Table 5 Distribution of university spin-offs by university/business location

State	By university location			By business location			Net gain (b)–(a)
	In-state spin-offs	Spin-offs moved out	Total (a)	In-state spin-offs	Spin-offs moved in	Total (b)	
California	177	18	195	177	113	290	95
Massachusetts	94	38	132	94	25	119	−13
New York	20	26	46	20	10	30	−16
North Carolina	25	8	33	25	6	31	−2
Pennsylvania	17	14	31	17	7	24	−7
Illinois	13	12	25	13	3	16	−9
Texas	16	9	25	16	15	31	6
Georgia	11	4	15	11	6	17	2
Washington	13	2	15	13	8	21	6
Colorado	7	4	11	7	4	11	0
Maryland	2	8	10	2	7	9	−1
Michigan	7	2	9	7	2	9	0
Ohio	4	5	9	4	2	6	−3
Arkansas	0	8	8	0	0	0	−8
Indiana	2	6	8	2	0	2	−6
Minnesota	7	1	8	7	5	12	4
Wisconsin	4	4	8	4	0	4	−4
Virginia	3	4	7	3	9	12	5
Connecticut	4	2	6	4	4	8	2
Missouri	2	4	6	2	0	2	−4
Utah	3	3	6	3	0	3	−3
Florida	1	4	5	1	4	5	0
New Jersey	3	2	5	3	6	9	4
Rode Island	3	2	5	3	1	4	−1
Tennessee	2	3	5	2	1	3	−2
New Mexico	2	2	4	2	2	4	0
Alabama	1	2	3	1	1	2	−1
Washington, D.C.	0	3	3	0	0	0	−3
West Virginia	0	3	3	0	0	0	−3
Kentucky	1	1	2	1	0	1	−1
Louisiana	0	2	2	0	0	0	−2
Oklahoma	1	1	2	1	0	1	−1
Delaware	1	0	1	1	0	1	0
Hawaii	0	1	1	0	0	0	-1
Iowa	0	1	1	0	1	1	0
Nebraska	1	0	1	1	0	1	0
New Hampshire	1	0	1	1	2	3	2
Oregon	1	0	1	1	5	6	5
Vermont	0	1	1	0	0	0	−1

Table 5 continued

State	By university location			By business location			Net gain (b)–(a)
	In-state spin-offs	Spin-offs moved out	Total (a)	In-state spin-offs	Spin-offs moved in	Total (b)	
Arizona	0	0	0	0	5	5	5
Nevada	0	0	0	0	1	1	1
Total	449	210	659	449	255	704	45[a]

[a] Net gains do not add up to zero because 45 spin-offs are associated with foreign institutions

spin-offs from Massachusetts universities ended up in other states. At the same time, 25 spin-offs moved into Massachusetts from the rest of the nation, resulting in a net loss of 13 university spin-offs. New York, the number three state in terms of total VC, has an even worse record with a net loss of 16 university spin-offs. Other states with a substantial net loss include Illinois (−9), Arkansas (−8), Pennsylvania (−7), and Indiana (−6).

Arizona and Arkansas represent two extreme cases. Arizona produced no academic entrepreneurs but ended up with five university spin-offs, all of which were founded by academic entrepreneurs from other states. In contrast, nine university employees in Arkansas founded eight university spin-offs, but none stayed in Arkansas and none entered from other states, leaving Arkansas with no venture-backed university spin-offs.

4 Performance of university spin-offs: multivariate analyses

This section investigates whether university spin-offs are significantly different from other start-ups in terms of VC financing, survival rate, initial public offering, profitability, and employment size. As mentioned above, the VentureOne data cover all companies that ever received equity investment from VC firms between the first quarter of 1992 and the fourth quarter of 2001. Although most of the venture-backed companies in the database are start-ups, some were self-sustaining for many years and only started to seek VC when they considered developing new products or moving into new markets. Others among these older companies accomplished only mediocre performance and relied on VC for a restart. These companies, which were founded long before 1992 but received VC after 1992 and showed up in the VentureOne data, should not be treated as representative venture-backed companies. If this highly selective group of companies were to be included in the sample, the analysis of firm performance would be biased. Given that the overall sample is quite large, I choose to exclude all companies founded in or before 1990 from the empirical analysis in this section.

4.1 University spin-offs versus non-spin-offs: a simple comparison

Table 6 compares an average university spin-off with an average firm that is not founded by university employees. Simple *t*-tests are conducted to show whether the differences in means are statistically significant. On average, university spin-offs raise significantly less money in a round of VC financing (the difference is $0.93 million). University spin-offs also raise less total VC, although the difference is not statistically significant. I also examine firm survival rate. A firm is defined as surviving if it is still in business by the end of the sample period. Thus surviving firms include those that have been acquired by other firms.[18] University spin-offs have a significantly higher survival rate: Whereas 94.4% of university spin-offs founded after 1990 were still in business by the end of 2001, only 87.8% of other firms survived. About 8% of the start-ups founded after 1990 had completed an IPO by the end of 2001. Whether a firm is a university spin-off makes no difference to the probability of completing an IPO. However, a university spin-off does show a difference in profitability: Only 2.9% of university spin-offs have ever made a profit, compared to 5.8% of other venture-backed firms.[19] In terms of average employment, university spin-offs are significantly smaller, with 58 employees compared to 84 employees at other firms.[20] These results in Table 6 call for further investigation because many confounding factors are not considered in this simple comparison.

4.2 Multivariate analyses

I conduct a series of multivariate regression analyses to compare university spin-offs with other venture-backed start-ups. The dependent variables include the amount of VC raised in a single round of financing, total amount of VC raised, whether a start-up has survived, whether a start-up has completed an IPO, whether a start-up has ever made some profit, and the employment size of a start-up.[21] The key independent variable of interest is the dummy variable indicating whether a start-up is a university spin-off.

Using the VentureOne data, I construct a set of control variables, including the following:

Start-up age. Start-up age is measured in months. All of the performance variables are expected to be correlated with start-up age. An older start-up tends to be larger and to need more capital, and thus tends to raise more money in a single round of financing and in total. An older cohort of start-ups is also more likely to have gone out of business, to have completed an IPO, and to have made some profit. In addition, an older start-up is expected to have more employees.

Whether started after 1995. The sample analyzed in this section includes firms founded during 1991–2001. The second half of this period is distinctively characterized by the Internet revolution. Internet technology spurred a large surge of high-tech entrepreneurship

[18] In corporate demography literature, a firm is considered as not surviving if it is acquired by another firm (see, for example, Carroll and Hannan 2000). Here I define "survival" more broadly and count acquired firms as surviving firms. An acquired firm, although it has lost its identity, is likely to retain its personnel and technology and continue to operate. From an economic point of view, it is still alive.

[19] The VentureOne data only indicate whether a firm has ever made a profit; there is no information about the amount of the profit or loss.

[20] Employment here refers to the employment level at the end of the sample period (fourth quarter of 2001). This comparison of employment is done only for firms that were still alive and privately held by the end of 2001. Employment information of other firms is not "current" because VentureOne would stop updating it if the firm was out of business, went public, or was acquired by another firm.

[21] Some of the performance variables clearly measure desirable outcomes from a start-up's (or its founder's) perspective. For example, one can rather confidently assume that a start-up's founder wants to build a surviving and profitable firm. However, raising the most VC may or may not be a start-up founder's goal. After all, the founder has to give up a share of the firm in exchange for VC investment. In some cases, it might be a better strategy for the entrepreneur to rely more on alternative sources of capital. One can only say that all else being equal, start-ups receiving more VC tend to be the more successful ones.

Table 6 Comparing venture-backed university spin-offs with other venture-backed start-ups

	Non-spin-offs (1)	University spin-offs (2)	T-Test Statistic H_0: (1)–(2) = 0
VC money raised per round ($ millions)[a,b]	10.45 (16.28)	9.52 (13.16)	2.19*
Sample Size	12,113	1,582	
Total VC money raised ($ millions)[a,b]	25.56 (34.99)	23.55 (29.06)	1.36
Sample size	4,663	606	
Survival rate[b]	0.878 (0.327)	0.944 (0.231)	−4.96**
Sample size	5,110	655	
Percentage completing IPO[b]	0.0765 (0.266)	0.0763 (0.266)	0.016
Sample size	5,110	655	
Percentage ever profitable[b]	0.0579 (0.234)	0.0290 (0.168)	3.07**
Sample size	5,109	655	
Average employment[c]	83.81 (169.1)	58.22 (84.78)	3.26**
Sample size	3,150	483	

[a] In 1996 dollars

[b] Sample includes all firms founded during 1991–2001. Note that venture-backed firms are included in the VentureOne database as long as they received equity investment from venture capital firms during 1992–2001. This means that some firms in the database were founded well before 1992. Given that it is very uncommon for a start-up to complete a round of venture capital financing within a year of its inception, it is reasonable to assume that all the venture-backed firms founded in 1991 were captured in the sample. Yet firms in the VentureOne database with a founding date earlier than 1991 must be a selective sample in that those obtained venture capital quickly would not show up in the VentureOne database. For this reason, firms founded before 1991 are dropped for this calculation

[c] Sample includes firms founded in or after 1991 and still privately held by 2001, the end of the sample period. Firms founded before 1991 are dropped for this calculation

Standard deviations are in parentheses. * Significant at 5% level. ** Significant at 1% level

and VC investment.[22] Start-ups founded in this period may be of lower quality because of relatively easier access to VC. This dummy variable is thus expected to pick up some of the effect of the overinvestment during the Internet bubble period.

Early-stage financing. I calculated *the start-up age at the first round of VC financing* and *the amount of venture money raised in the first round*. When a start-up receives a great deal of VC at an early stage, either it has an impressive business model or it has an average business plan but happens to have easy access to capital for some other reasons. In either case, the early access to capital may buy the start-up some first-mover advantage. Such a start-up is expected to outperform others in terms of survival, IPO, profitability, and employment.

Year dummies. In some regressions, the closing year of VC rounds is used to control for the trend of VC investment; in some others, the start year of companies is used to control for the cohort effect.

[22] For example, total VC investment in the U.S. amounted to $88.9 billion in 2000, compared to only $6.8 billion in 1995. VC investment in the late 1990s is often described as "too much money chasing too few good ideas."

Industry dummies. No matter which performance measure is used, start-ups in different industries are expected to perform differently. For example, start-ups in the telecommunication industry are capital-intensive and thus will likely raise more venture capital. Similarly, start-ups in the biopharmaceutical industry usually spend many years on research and development before putting the first product on the market, and thus these start-ups might remain in business longer simply because of their longer product life cycle. Based on VentureOne's industry classification, I construct 16 dummy variables to control for industry effects.

VC round dummies. To indicate the stage of investment, VentureOne categorizes VC rounds into different classes such as seed round, first round, second round, later round, and so on. Naturally, later rounds of financing tend to raise more money for a start-up because its growth potential is clearer and its need becomes higher. Therefore, it is necessary to control for this effect when studying the amount of VC raised in each round.

High-tech center dummies. Because venture capitalists are concentrated in a few high-tech centers, start-ups in those regions are expected to have easier access to VC. As Zhang (2007) shows, start-ups in Silicon Valley tend to receive VC at a younger age, to raise more money in each round of financing, and to complete more rounds of financing than start-ups elsewhere; and this better access to VC has a significant effect on start-up performance. Thus, I construct a few location dummies to indicate whether a start-up is in a high-tech center such as Silicon Valley, the rest of the San Francisco Bay area, Boston, New York, Seattle, or Washington, D.C. See the Appendix for the geographic definition of these high-tech centers.

A series of regression analyses are conducted to examine whether university spin-offs exhibit significantly different performance compared to other venture-backed start-ups. For each performance measure under examination, control variables are added sequentially to the regression to show their relative importance in explaining observed differences. In each case, I run either OLS or logit regressions depending on the nature of the dependent variable.[23]

4.2.1 Amount of VC raised

Table 7 presents the OLS regression analysis of VC financing, with the amount of capital raised in each round as the dependent variable. As shown in Table 6, university spin-offs raise an average of \$0.93 million less than other venture-backed start-ups. Model (1) in Table 7 shows that the difference is about the same size and still statistically significant even after controlling for start-up age at VC deal and whether founded after 1995. Model (2) adds the industry dummies to the regression, which reduces the difference substantially and makes it statistically insignificant. This result persists as more control variables are included in the regression. Although not presented in Table 7, alternative specifications show that adding VC round dummies alone to Model (1) will make the university spin-off variable statistically insignificant, but adding the closing year dummies or the high-tech center dummies alone to Model (1) would not have the same effect. These results suggest that university spin-offs appear to raise less venture money primarily because they are overrepresented in certain industries and early VC rounds that are associated with smaller VC deals.

The models in Table 7 consistently show that firms started after 1995 received more VC, which makes sense because a large amount of VC flowed into high-technology

[23] In all cases where the independent variable is a dummy variables, probit models are also estimated, which give qualitatively similar results as the logit models.

Table 7 Venture capital financing, OLS (Dependent Variable: venture capital raised in any round (millions of 1996 dollars))

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Constant	0.535 (0.423)	−4.003** (2.335)	0.055 (2.269)	3.163 (2.215)	2.580 (2.195)
University spin-off	−0.920* (0.440)	−0.257 (0.412)	−0.063 (0.394)	−0.288 (0.385)	−0.299 (0.382)
Started after 1995	7.604** (0.402)	7.354** (0.413)	6.012** (0.396)	2.780** (0.562)	2.800** (0.560)
Start-up age at VC deal closing date	0.145** (0.007)	0.157** (0.007)	0.067** (0.008)	0.028** (0.010)	0.032** (0.011)
Industry dummies	N	Y	Y	Y	Y
VC round dummies	N	N	Y	Y	Y
VC deal closing year dummies	N	N	N	Y	Y
High-tech center dummies	N	N	N	N	Y
R^2	0.038	0.080	0.125	0.161	0.163
Number of observations	13,502	13,502	13,502	13,502	13,502

Standard errors, reported in parentheses, are robust to clustering within a venture-backed firm. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

industries during the Internet boom in the latter half of the decade. These models also show that, as expected, older companies raise more money in each round of VC financing.

Table 8 presents the regression results on total VC raised by each start-up. The coefficient of university spin-off is still negative but never statistically significant. A comparison of Model (3) with Models (1) and (2) shows that the coefficient of university spin-off becomes considerably smaller once industry dummies are included in the regression. Again, this implies that university spin-offs appear to raise somewhat less VC

Table 8 Venture capital financing, OLS (Dependent Variable: total venture capital raised (millions of 1996 dollars))

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	−3.180** (0.959)	−35.99** (3.602)	−37.55** (7.193)	−38.21** (7.200)
University spin-off	−2.211 (1.309)	−2.389 (1.286)	−0.701 (1.317)	−0.694 (1.320)
Start-up age at last VC round	−0.049* (0.022)	0.226** (0.030)	0.232** (0.030)	0.243** (0.030)
Total rounds of VC completed	12.00** (0.294)	14.80** (0.376)	14.40** (0.366)	14.36** (0.366)
Start year dummies	N	Y	Y	Y
Industry dummies	N	N	Y	Y
High-tech center dummies	N	N	N	Y
R^2	0.255	0.286	0.335	0.335
Number of observations	5,141	5,141	5,141	5,141

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

Table 9 Survival of venture-backed start-ups, Logit (Dependent Variable: 1 if survived)

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	1.914** (0.098)	6.402** (1.611)	5.540** (1.703)	5.568** (1.705)
University spin-off	0.877** (0.185)	0.838** (0.186)	0.497** (0.192)	0.485* (0.192)
Start-up age	−0.0006 (0.002)	−0.037** (0.013)	−0.040** (0.013)	−0.040** (0.013)
Start-up age at closing date of first round VC	0.008** (0.003)	0.010** (0.003)	0.013** (0.003)	0.012** (0.003)
Money raised at first round VC (1996 dollars)	−0.005 (0.005)	−0.006 (0.005)	−0.005 (0.005)	−0.005 (0.005)
Start year dummies	N	Y	Y	Y
Industry dummies	N	N	Y	Y
High-tech center dummies	N	N	N	Y
Pseudo R^2	0.011	0.028	0.056	0.058
Number of observations	5,338	5,338	5,323	5323

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

primarily because they tend to be in industries with smaller VC deals. Unexpectedly, Model (1) shows that an older start-up is associated with a smaller amount of total VC raised. This is likely due to the fact that older firms completed their early rounds of VC financing in the early 1990s, when VC money was much scarcer and average deal size was much smaller. Indeed, once starting years are controlled for in Models (2)–(4), start-up age always has a positive and statistically significant effect on total VC raised. As expected, all models in Table 8 show that more VC rounds imply more VC money raised. While an average round of VC financing raises \$9.5–10.5 million as reported in Table 6, results in Table 8 show that an extra round of financing adds more than \$14 million to the total amount of VC raised by a start-up, apparently because later rounds are larger.

4.2.2 Survival rate

Logit models are estimated to study the probability of survival for these venture-backed start-ups.[24] The results are presented in Table 9. Under all four specifications, the university spin-off dummy has a positive and statistically significant coefficient. That is, university spin-offs are more likely to survive. The difference in survival rate between university spin-offs and other venture-backed companies becomes substantially smaller when industry dummies are included in Model (3). Adding high-tech center dummies in Model (4) continues to reduce the difference, but it is still statistically significant at the 5% level. The coefficient of the university spin-off dummy in Model (4) is 0.485. It implies

[24] For survival analysis, hazard models are preferred over logit models. However, for most of the start-ups that were out of business, the VentureOne data indicate only that they no longer existed by the end of 2001 but do not specify an exact exit date. Thus it is impossible to construct the time-to-event variable to estimate standard hazard models. For similar reasons, logit models instead of hazard models are estimated for IPO analysis, as will be shown below.

that the odds of survival for non-spin-offs are close to 40% lower than for university spin-offs, a difference that seems to be also economically significant.[25]

The higher survival rate of university spin-offs may be explained by academic entrepreneurs' higher opportunity costs. Researchers in academia, especially those in highly-ranked research universities, pursue an extremely competitive career. To succeed in such institutions requires devotion, concentration, and hard work. For this reason, when an academic researcher decides to take a large amount of time or, in many cases, to initiate a shift in career path to create a business, it is very likely that he or she has a viable business plan. In other words, an academic entrepreneur has a lot more to lose than other individuals if the start-up quickly goes out of business. Thus, an academic entrepreneur must have thoroughly examined the business plan and market conditions before the firm-founding decision is made. And this "due diligence" could give venture-backed university spin-offs a better chance of survival.

Another possible explanation of the higher survival rate of university spin-offs is their technology advantage. A university spin-off almost always embodies a piece of knowledge created or acquired by its founders in an academic setting. This knowledge, which is either patented or tacit in nature and thus diffuses slowly, may give a university spin-off a competitive edge that enhances its odds of survival.

A third possible explanation is that university spin-offs and academic entrepreneurs benefit from incubatory services provided by universities. State policymakers have long recognized the economic potential of high technology start-ups. Many states, in collaboration with universities and network organizations, have implemented policies to support technology start-ups (Biotechnology Industry Organization 2004). The most commonly used policy is providing support, financial or otherwise, to university faculty members for commercializing academic research. For example, in Georgia, the Advanced Technology Development Center (ATDC) has a Faculty Research Commercialization Program that provides funding to university researchers who want to commercialize discoveries by starting companies. ATDC and the Georgia Research Alliance (GRA) together with research universities in the state have created several biotechnology incubators, including The Center for Applied Genetics Technology at the University of Georgia, EmTech Biotechnology Development, Inc. (jointly launched by Emory University, Georgia Tech, ATDC, and GRA), and CollabTech at Georgia State University. Massachusetts is another state where many incubators have been established to facilitate academic entrepreneurship, including Massachusetts Biotechnology Research Park (located adjacent to the University of Massachusetts Medical Center), BioSquare (a private research park affiliated with the Boston University School of Medicine and Boston Medical Center), Tufts Science park (located on the campus of the Tufts University School of Veterinary Medicine), and University Park at MIT (located on 27 acres next to MIT, one of the first biomedical parks in the nation). All these incubators aim to assist university researchers who intend to start technology firms, which may have helped enhance the chance of survival for university spin-offs.[26]

[25] The odds of survival are defined as the ratio of probability of surviving to the probability of not surviving. Under a logit model, it is simply $e^{\alpha+x\beta}$. Thus the ratio of these two odds (for non-spin-offs and spin-offs) is $e^{(x_1-x_2)\beta} = e^{-1*0.485} = 0.616$.

[26] Results in Tables 7–10 together point to an interesting phenomenon: University spin-offs have a higher chance to survive despite relatively lower financial support from VC (the latter result being persistent in Tables 7–9 although in most cases statistically insignificant). This may also be explained by the incubatory support university spin-offs tend to receive from parent universities and other local organizations. In addition, this result is also consistent with the theory that the asset parsimony strategy and growing by bootstrapping often help a start-up to succeed (Hambrick and MacMillan 1984; Venkataraman 2003).

Even with all these plausible explanations, one still cannot rule out the possibility that not enough controls are included in the regressions in Table 9. As Models (1)–(4) show, adding more control variables not only lowers the effect of the university spin-off variable, but also reduces its statistical significance. Thus, it is possible that university spin-offs show a higher survival rate only because some important control variables are missing from this analysis. For example, although industry dummies are included in the regression, differences within an industry are not accounted for. More specifically, even within the biotech industry, drug development firms may have a longer product life cycle than other firms. It is common for a start-up to spend more than ten years to develop a drug and put it on the market. But a start-up specializing in bioinformatics could behave just like a software company: Its business may prove unviable in a fairly short period of time and it may go out of business just a few years after its inception. Thus, a drug discovery start-up may not be more successful, but its longer product cycle does allow it to stay in business longer, which translates into a higher survival rate. Unfortunately, the VentureOne data do not contain information detailed enough to allow for controlling for such within-industry differences.

Results in Table 9 also show that start-up age, as expected, is negatively correlated with survival rate: A larger proportion of the older cohorts have gone out of business. Receiving venture capital at a younger age has a significantly negative effect on survival, possibly because these firms are not carefully screened by venture capitalists. Although quicker access to capital is expected to give some first-mover advantage to start-ups, it seems that the advantage is not large enough to offset the effect of poor business plans admitted by quick investment.

4.2.3 Initial public offering

Table 10 presents a logit analysis of the probability of initial public offering among venture-backed start-ups. It shows that university spin-offs and other firms have a similar chance of issuing an IPO. The university spin-off dummy is not statistically significant under any model specification. It is expected that a larger proportion of older firms should have completed an IPO, but that effect is captured by the start-year dummies rather than the start-up age variable once the former are included in the regression.

Start-ups that have access to VC at a younger age and receive a larger amount of venture money in the first round are more likely to complete an IPO. This is consistent with the first-mover advantage hypothesis. That is, a start-up that secures venture support at a very early stage can grow quickly and gain a head start over competing start-ups. In the rapidly growing high-tech industries, the first-mover advantage is crucial for a successful start-up. Consider examples such as Yahoo!, Netscape, Amazon.com, and eBay. These are among the most successful Internet companies in the early years of the Internet boom. In each case, their status as a first mover might have played an equally important role in their success as their technological advantage. Another possible explanation of the relationship between a high IPO rate and quick access to VC is that only the most promising start-ups receive financing at a very early stage. However, it is difficult to reconcile this hypothesis with the results shown in Table 9, which indicates that a quicker access to venture capital is actually associated with a lower survival rate.

Table 10 Initial public offering of venture-backed start-ups, Logit (Dependent Variable: 1 if completed an IPO)

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	−4.924** (0.156)	1.511 (1.893)	−0.453 (2.179)	−0.742 (2.196)
University spin-off	−0.075 (0.173)	−0.0002 (0.171)	0.116 (0.187)	0.140 (0.189)
Start-up age	0.047** (0.002)	−0.012 (0.015)	−0.006 (0.015)	−0.004 (0.016)
Start-up age at closing date of first round VC	−0.039** (0.003)	−0.036** (0.003)	−0.038** (0.003)	−0.037** (0.004)
Money raised at first round VC (1996 dollars)	0.023** (0.005)	0.038** (0.006)	0.035** (0.006)	0.036** (0.006)
Start year dummies	N	Y	Y	Y
Industry dummies	N	N	Y	Y
High-tech center dummies	N	N	N	Y
Pseudo R^2	0.190	0.201	0.228	0.240
Number of observations	5,338	4,579	4,579	4,579

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

One may argue that these regressions for IPO and for survival rate presented above should include the total amount of VC instead of the amount of the first round VC as an independent variable. The idea is that raising more VC in total should help a start-up to survive and succeed (in terms of going public). I tried these alternative specifications. In each case, the coefficient of the university spin-off dummy is not qualitatively affected: Its sign was unchanged in all the regressions; it remained statistically significant in the regressions for survival; and it remained statistically insignificant in the regressions for IPO. I prefer the specifications in Tables 9 and 10 (using the amount of first-round VC rather than the total) over the alternative specifications for the following reason. It is common practice that venture capitalists make staged investment to start-ups, with later investment decisions based on performance. By doing so, venture capitalists are trying to set up the right incentive structure to encourage the entrepreneur to work hard. Because of this practice, performance and the total amount of VC should be (and indeed are) highly correlated. However, it is more reasonable to think that the direction of causality runs the other way, i.e., surviving longer leads to more VC.

4.2.4 Profitability

Table 11 presents a logit analysis of the probability of making a profit. The results in the first two columns are consistent with those in Table 6. That is, university spin-offs are less likely to make any profit. However, once industry dummies are controlled for (in Models (3)–(4)), the statistical significance of the university spin-off dummy becomes much lower, although its coefficient remains negative. This result suggests that to a great extent university spin-offs show a low probability of making profit because they are disproportionally concentrated in industries such as the biopharmaceutical industry in which it takes many more years for a start-up to develop a marketable product and become

Table 11 Profitability of venture-backed start-ups, Logit (Dependent Variable: 1 if ever made a profit)

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	−4.404** (0.160)	−4.111 (2.217)	−2.601 (2.334)	−2.270 (2.344)
University spin-off	−0.781** (0.250)	−0.769** (0.251)	−0.510 (0.262)	−0.488 (0.264)
Start-up age	0.025** (0.002)	0.021 (0.018)	0.015 (0.018)	0.015 (0.018)
Start-up age at closing date of first round VC	−0.0016 (0.003)	−0.0013 (0.003)	−0.001 (0.003)	−0.004 (0.003)
Money raised at first round VC (1996 dollars)	0.019** (0.005)	0.019** (0.005)	0.020** (0.006)	0.019** (0.006)
Start year dummies	N	Y	Y	Y
Industry dummies	N	N	Y	Y
High-tech center dummies	N	N	N	Y
Pseudo R^2	0.078	0.080	0.124	0.136
Number of observations	5,338	5,338	5,328	5,328

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

profitable.[27] When start year dummies are excluded from the regression (Model (1)), start-up age (measured in months) has a positive and statistically significant coefficient, meaning that older firms have a higher probability of making some profit. Once starting year dummies are included (in Models (2)–(4)), this age effect is largely captured by the year dummies. The most consistent result in Table 11 is that a start-up receiving more money at the first VC round is more likely to have made some profit, which is again consistent with the hypothesis that early-stage VC money gives the start-up some first-mover advantage.

4.2.5 Employment

Table 12 presents the OLS regression results for start-up employment. This analysis focuses exclusively on venture-backed start-ups that were still privately held at the end of the sample period, because VentureOne stops updating employment information once a start-up's ownership status changes. As shown in Table 6, university spin-offs are significantly smaller than other venture-backed start-ups in terms of employment. This difference persists even after controlling for start-up age, early access to VC, and start year. But adding industry dummies (in Model (3)) wipes the difference away. The coefficients of industry dummies (not shown in Table 12) indeed show that major industries with a higher concentration of university spin-offs—such as the biopharmaceutical, medical devices, medical information system, and semiconductor industries - all have a relatively smaller employment size. This does not necessarily mean that firms in these industries create fewer jobs. It is possible that some of these firms grow slower in the early years because they focus on

[27] The measure of profitability used in this study might appear to be an imperfect one because a firm that loses money for many years does not necessarily make less profit over a longer period of time. For example, a biopharmaceutical company may lose a large amount of money for many years. However, once it sees profit, it can also continuously generate a large amount of profit for many years, which makes it more profitable than many other companies over its whole lifetime.

Table 12 Employment of privately-held start-ups, OLS (Dependent Variable: number of employees)

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	−5.938 (6.013)	−12.45 (97.86)	19.29 (102.9)	29.08 (102.9)
University spin-off	−23.87** (7.800)	−23.29** (7.797)	−3.744 (7.999)	−3.548 (8.014)
Start-up age	1.876** (0.130)	1.505* (0.768)	1.315 (0.745)	1.310 (0.745)
Start-up age at closing date of first round VC	−1.579** (0.178)	−1.511** (0.181)	−1.383** (0.180)	−1.463** (0.183)
Money raised at first round VC (1996 dollars)	4.756** (0.320)	4.804** (0.320)	4.373** (0.314)	4.371** (0.314)
Start year dummies	N	Y	Y	Y
Industry dummies	N	N	Y	Y
High-tech center dummies	N	N	N	Y
R^2	0.100	0.107	0.172	0.175
Number of observations	3,437	3,437	3,437	3,437

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

R&D. They may become much larger in the long run after they enter the stage of mass production.

It is a robust result that start-ups receiving a large amount of VC at an early stage tend to have significantly more employees. Again, this may reflect the first-mover advantage the early stage VC helps create. However, it is equally possible that early stage VC money only flows to those fast-growing start-ups that show a great potential for financial success. Given that venture capitalists look at firm performance to decide on VC funding, the coefficient of this variable must be biased and has to be interpreted with caution.[28]

4.2.6 Software and biopharmaceutical industries

Because university spin-offs are concentrated in software and biopharmaceutical industries, all the regressions are run separately using the sub-sample from each of these two industries. The purpose of this analyses is to check whether the results observed for the whole sample still hold in a particular industry. Because industry dummies are crucial in explaining away some of the earlier findings, these regressions within an industry are in a sense a cleaner control than simply adding industry dummies in the regression. The results are reported in Tables 13 and 14, respectively, for software and biopharmaceutical industries. Perhaps because of much smaller samples used for these regressions, the coefficient of the university spin-off dummy is never statistically significant. In Table 13, results of the software industry parallel those of the whole sample in that the coefficient of the university spin-off dummy always has the same sign as in the regressions using the whole sample. But in Table 14, for the biopharmaceutical industry, the sign of the

[28] Economists have developed various strategies (such as the use of instrumental variables or regression discontinuity design) that rely on richer data and better research designs to correct this kind of endogeneity bias. However, the VentureOne data are not rich enough to allow for such sophisticated econometric analyses.

Table 13 Performance of venture-backed start-ups in the software industry

	VC in a single round (OLS)	Total VC (OLS)	Survival (Logit)	IPO (Logit)	Profitability (Logit)	Employment (OLS)
Constant	2.960 (3.522)	–			37.74** (4.948)	4.630 (3.601)
−2.794 (4.082)	−6.814 (5.012)	78.68 (74.48)				
University spin-off	−0.854 (0.705)	−1.901 (1.979)	0.823 (0.432)	0.402 (0.366)	−0.681 (0.613)	−4.682 (6.213)
Started after 1995	3.381** (0.868)					
Start-up age at VC deal closing date	0.083** (0.015)					
Start-up age at last VC round		0.294** (0.045)				
Start-up age			−0.027 (0.029)	0.020 (0.033)	0.040 (0.040)	0.243 (0.583)
Start-up age at closing date of first round VC			0.011 (0.006)	–	0.032** (0.007)	0.003 (0.007)
−0.842** (0.147)						
Money raised at first round VC			−0.020 (0.012)	0.007 (0.033)	0.08 (0.018)	3.160** (0.430)
Total rounds of VC completed		12.39** (0.584)				
VC round dummies	Y	N	N	N	N	N
VC deal closing year dummies	Y	N	N	N	N	N
Start year dummies	N	Y	Y	Y	Y	Y
High-tech center dummies	Y	Y	Y	Y	Y	Y
(Pseudo) R^2	0.126	0.318	0.030	0.179	0.127	0.186
Number of observations	3,626	1,413	1,450	944	1,448	968

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

All financial data are in 1996 dollars

coefficient reversed in some regressions. The most interesting result from this industry level analysis is that university spin-offs still show a higher probability of survival even within the software industry (with a coefficient that is statistically significant at the 10% level). This suggests that university spin-offs' higher survival rate observed in the whole sample is not entirely driven by the concentration of such firms in the biopharmaceutical industry.

Overall, I find that university spin-offs differ from other start-ups only in terms of survival rate. Simple comparisons of sample means show that university spin-offs raise less venture money in a round of VC financing, are less likely to make any profit, and have fewer employees. But such differences become statistically insignificant once some control variables are included in the multivariate analyses. In all three cases, it is the industry dummies that explain away the differences.

Table 14 Performance of venture-backed start-ups in the biopharmaceutical industry

	VC in a single round (OLS)	Total VC (OLS)	Survival (Logit)	IPO (Logit)	Profitability (Logit)	Employment (OLS)
Constant	4.369 (3.004)	−15.55 (9.667)	2.331 (2.468)	–	8.969** (1.622)	−15.82** (5.461)
89.14 (68.41)						
University spin-off	0.353 (0.711)	0.944 (2.373)	0.250 (0.783)	0.102 (0.389)	−0.899 (0.943)	1.962 (3.801)
Started after 1995	1.027 (1.370)		0.631 (1.497)	2.447** (0.767)	3.862 (2.196)	
Start-up age at VC deal closing date	0.039 (0.025)					
Start-up age at last VC round		0.132 (0.084)				
Start-up age			−0.004 (0.023)	0.073** (0.015)	0.123** (0.048)	−0.335 (0.548)
Start-up age at closing date of first round VC			0.054 (0.047)	–	0.035** (0.013)	−0.026 (0.027)
−0.426** (0.136)						
Money raised at first round VC			0.307 (0.246)	0.082** (0.025)	0.034 (0.084)	0.955** (0.327)
Total rounds of VC completed		10.03** (0.989)				
VC round dummies	Y	N	N	N	N	N
VC deal closing year dummies	Y	N	N	N	N	N
Start year dummies	N	Y	N	N	N	Y
High-tech center dummies	Y	Y	N	Y	N	Y
(Pseudo) R^2	0.207	0.476	0.110	0.232	0.276	0.323
Number of observations	897	296	306	292	306	227

Standard errors are in parentheses. * Significant at 5% level. ** Significant at 1% level

N = dummy variables are not included in regression. Y = dummy variables are included in regression

All financial data are in 1996 dollars

As noted above in the data section, the regression results in this paper are subject to potential sample selection biases. In particular, the empirical analysis focuses exclusively on venture-backed firms whose founder's biographical information is available in the VentureOne database. This sample may not be representative of the population given that it may be easier for VentureOne to gather the founder information for certain types of firms than others. Indeed, as shown in Table 1, VentureOne tends to have the founder information available for surviving firms, which may bias the finding that university spin-offs have a higher survival rate. Unfortunately, there is not enough information in the VentureOne data that could be used to estimate Heckman-type models to correct for the potential selection biases.[29]

[29] In principle, I can estimate Heckman-type sample selection models by adding a selection equation to explain what types of firms tend to have founder information available. And indeed I tried that. However, VentureOne data contain limited information on firm characteristics and most of such characteristics are

It is thus useful to think about the direction of the biases, if they indeed exist. It is reasonable to assume that the distribution of surviving time is bell-shaped for both university spin-offs and other venture-backed firms. Because both distributions are bounded on the left at zero, the distribution for university spin-offs is most likely to have a thinner density on the left side given that they appear to survive longer. If firms with a shorter surviving time tend to have founder information missing and thus are selected out, this implies that a smaller proportion of university spin-offs on the left side of the distribution have been excluded from the study sample. In that case, the sample selection bias is actually against finding a significantly higher survival rate for university spin-offs. This suggests that the survival rate difference between university spin-offs and other venture-backed firms may be even higher than observed. Therefore, the finding that university spin-offs have a higher survival rate is likely to be qualitatively correct.

5 Conclusions

Universities, as the center for knowledge creation and dissemination and a major force of technological innovation, are increasingly recognized as an important driver of economic growth (Rosenberg and Nelson 1994). Universities contribute to the economy through various direct and indirect channels, one of which is the entrepreneurial activities of academic scientists. Despite the well-recognized value of studying university spin-offs, research on this topic is continuously constrained by the limited availability of data. This paper examines VC-backed university spin-offs using a large sample extracted from the VentureOne database. I take advantage of the rich information in the VentureOne data to characterize academic entrepreneurs and university spin-offs. I also conduct a series of multivariate analyses comparing university spin-offs with other venture-backed start-ups using various performance measures. The data have enabled me to arrive at a number of key findings.

First, venture-backed university spin-offs are common and concentrated in certain industries. Close to 9% of venture-backed entrepreneurs have been affiliated with academic institutions. University spin-offs founded by these entrepreneurs account for 11% of the venture-backed start-ups in the sample. A majority of the academic entrepreneurs specialize in engineering, and most of their businesses are in the life science and information technology industries. The most striking finding is that more than half of the venture-backed start-ups in the biopharmaceutical industry are university spin-offs. Previous research has shown that academic entrepreneurs played an important role in the biotech industry during its inception (see, for example, Kenney 1986a, b). This study suggests that the involvement of academic entrepreneurs in the biotech industry has persisted. It also implies that the biotech industry has continuously relied on university research as a source of innovation.

Footnote 29 continued
discrete variables. Similarly, most of the control variables in the main equation are also discrete variables. As a result, the likelihood function of the sample selection model is not smooth and its maximum is difficult to find. This is particularly true for discrete performance outcome variables. I tried many different specifications for the selection equation and tried both probit and linear probability models for the main equation, but Stata could only complete the maximum-likelihood estimation for the simplest specifications of the equation for survival and IPO. For profitability, the estimation is impossible under any specifications. These exercises are not very informative about the magnitude of selection biases.

Second, to a great extent, technology transfer through university spin-offs is a local phenomenon. More than two-thirds of the university spin-offs are located in the same state as the parent university. Many conceivable factors could explain why academic entrepreneurs remain in the local area when they found firms, including the value of local networks and the feasibility of an informal start-up on a part-time basis (Cooper and Folta 2000). The motivation among other academic entrepreneurs who move to other states to start their businesses needs to be more systematically studied.[30] Anecdotal evidence suggests that the availability of venture capital might lure entrepreneurs away from their home base. Yet empirical data in this paper suggest that venture capital is not a sufficient determinant, since states rich in venture capital, such as Massachusetts and New York, have both experienced net losses of university spin-offs.

Third, after controlling for industry and other relevant factors, university spin-offs have a higher survival rate but exhibit no significant difference from other venture-backed firms in terms of the amount of VC money raised per round, total amount of VC raised, the possibility of completing an IPO, the probability of making a profit, or employment size. There are several possible reasons why university spin-offs tend to survive longer. It may be that the higher opportunity cost of academic entrepreneurs motivates them to engage in more self-screening before they create a company. It is also possible that university spin-offs are built around a truly advanced technology that enhances the company's chance of survival. And finally, incubatory and other support from parent universities or local governments may have also helped keep university spin-offs in business.

Whereas the large sample size of the VentureOne data is advantageous for comprehensive statistical analysis, the use of these data has its own limitations. First, the data require this study to focus exclusively on venture-backed university spin-offs, which represent a small subset of all the firms founded by academic entrepreneurs. These venture-backed firms may be the most prominent ones that contribute the most to economic growth, yet it is still desirable to study non-venture-backed university spin-offs in order to have a complete understanding of university spin-offs. Second, and perhaps more important, this paper's empirical findings are subject to potential selection biases because VentureOne's founder sample may not be random. Although the statistical techniques for correcting such biases are well developed, there is not enough information in the VentureOne data to allow for the estimation of selection models. These limitations, of course, can only be overcome in future research by collecting more and better data.

Appendix: Geographic definition of industrial clusters

Following the tradition established by regional institutions such as the Joint Venture: Silicon Valley Network, I define Silicon Valley as Santa Clara County and adjacent cities in Alameda, San Mateo, and Santa Cruz Counties.

[30] There is no lack of anecdotal accounts of start-up location choices. Through my personal communications with start-up founders, I find that quality of life, quality of labor pool, and availability of capital are the most frequently cited factors that affect the location of a start-up.

City	Zip Code
Santa Clara County	
All cities	All zip codes
Alameda County	
Fremont	94536–39, 94555
Newark	94560
Union City	94587
San Mateo County	
Atherton	94027
Belmont	94002
East Palo Alto	94303
Foster City	94404
Menlo Park	94025
Redwood City	94061–65
San Carlos	94070
San Mateo	94400–03
Santa Cruz County	
Scotts Valley	95066–67

Other regions are more loosely defined using area codes.

Region	Area code
San Francisco Bay Area	Silicon Valley, plus 408, 415, 510, 650, and 925 if not already in Silicon Valley
Boston	508, 617, 781, 978
New York	201, 212, 347, 516, 646, 718, 732, 845, 908, 914, 917, 973
Seattle	206, 253, 360, 425
Washington, D.C.	202, 240, 301, 571, 703

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