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Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999

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ABSTRACT

We examine two views of the creation of venture-backed start-ups, or "entrepreneurial spawning." In one, young firms prepare employees for entrepreneurship, educating them about the process, and exposing them to relevant networks. In the other, individuals become entrepreneurs when large bureaucratic employers do not fund their ideas. Controlling for firm size, patents, and industry, the most prolific spawners are originally venture-backed companies located in Silicon Valley and Massachusetts. Undiversified firms spawn more firms. Silicon Valley, Massachusetts, and originally venture-backed firms typically spawn firms only peripherally related to their core businesses. Overall, entrepreneurial learning and networks appear important in creating venture-backed firms.

THERE IS NOW A LARGE AND GROWING LITERATURE analyzing the factors that determine whether entrepreneurs raise venture capital funding (Hellmann and Puri (2000), Burton, Sørensen, and Beckman (2002)) and the factors that affect the terms of this financing (Gompers (1997), Kaplan and Strömberg (2003)). There is much less understanding of how these venture capital-backed entrepreneurs come to be entrepreneurs in the first place. In this paper, we try to fill this gap by examining the factors that lead to the creation of venture capital-backed entrepreneurs, a process we term "entrepreneurial spawning."

We examine two views of the spawning process. In one view, young firms prepare employees to be entrepreneurs by educating them about the entrepreneurial process and by exposing them to a network of entrepreneurs and venture capitalists. The prolific spawning of entrepreneurial firms by Fairchild Semiconductors and its descendents is a prominent example of "how entrepreneurial learning and networks may function," as Saxenian (1994,

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p. 112) writes. Fairchild was founded by eight engineers who left Shockley Semiconductor with $1.5 million in venture capital funding from Arthur Rock, one of the earliest (and later most successful) venture capitalists. While the "Treacherous Eight" succeeded as inventors of the first integrated circuit in 1959, the founders and other engineers soon began to leave Fairchild to begin firms of their own. Between 1957 and 1976, at least 23 out of 67 entrants to the semiconductor industry had at least one founder who worked for Fairchild (Braun and Macdonald (1982)), including Advanced Micro Devices, Intel, and National Semiconductor, almost all of which were based in Silicon Valley.

In this view, individuals already working for entrepreneurial firms, particularly those already backed by venture capitalists and located in hotbeds of venture capital activity—notably Silicon Valley and Massachusetts—may find launching their own venture less daunting than others for a number of reasons. First, working in such firms exposes would-be entrepreneurs to a network of suppliers of labor, goods, and capital, as well as to a network of customers (Saxenian (1994)). Because starting a new venture requires suppliers and customers to make relationship-specific investments before it is guaranteed that the venture will get off the ground, networks can be particularly useful in alleviating this chicken-and-egg problem (Hellmann (2002)). Second, the would-be entrepreneurs learn how to found companies by participating in the entrepreneurial process alongside other, more experienced entrepreneurs. Finally, individuals with a higher taste for risky activities may have already found their way to entrepreneurial firms, consistent with the sorting processes hypothesized by Jovanovic (1979), Holmes and Schmitz (1990), and Gromb and Scharfstein (2002). We refer to this depiction of entrepreneurial spawning as the "Fairchild view."

Another view[1] of the entrepreneurial spawning process is that individuals become entrepreneurs because the large bureaucratic companies for which they work are reluctant to fund their entrepreneurial ideas. The most prominent example of this is Xerox, which developed many of the key technologies underlying the personal computer, but which failed to commercialize these technologies (summarized in Hunt and Lerner (1995)). In 1969, Xerox chief executive Peter McColough commissioned the firm's head of research to build a new laboratory to provide the company with the technology to move the firm from being the leading office copier company to being the dominant supplier of information-intensive products (Chesbrough (2002)). The Palo Alto Research Center (PARC) was formed to house this group in 1970. The firm hired outstanding researchers for this new technical initiative, including physicists, mathematicians, materials scientists, computer system architects, and software engineers. PARC proved to be enormously fertile, inventing such technologies as laser printing, the ethernet, the graphical user interface, and personal distributed computing. Despite appeals by PARC leaders to invest in commercializing these innovations, the firm's Rochester, New York-based executives resisted

[1] These hypotheses are, of course, not exhaustive. For an evolutionary-based theory, for instance, see Klepper (2001).

such expenditures. Instead, the vast bulk of the value from these inventions was captured by employees who left Xerox to found companies such as Adobe Systems and 3Com as well as licensees such as Apple Computer.

There are at least three reasons why large, established firms might be more prone to spawn entrepreneurial ventures. We refer to this as the "Xerox view" of entrepreneurial spawning. First, established firms may be incapable of responding to radical technological changes that upset the established ways of organizing their businesses. Henderson (1993) presents evidence for the organizational incapacity of firms to respond to technological change. Using data from the semiconductor photolithography industry, she shows that incumbents were consistently slower than entrants in developing and introducing new technologies.

A second, related reason why large, established companies may spawn more is that high-level managers at these firms are incapable of evaluating these entrepreneurial opportunities because they fall outside the company's core line of business. Assessing these opportunities may also require the analysis of "soft information," which hierarchical organizations may have a hard time doing (Berger et al. (2002), Stein (2002)). Moreover, the internal capital market tends to favor established lines of business over less established but perhaps more promising businesses (Scharfstein (1998), Scharfstein and Stein (2000)). These arguments suggest that a considerable amount of entrepreneurial spawning should come from large established firms, where these problems are presumably most severe.

Finally, it is also possible that the level of entrepreneurial spawning would be high among these firms not because of any sort of inefficiency at these firms, but rather because these firms wisely choose to focus on their core business or "core competence." The wisdom of focusing on one's core competence has been a mainstay of management consulting since 1980s. It is also supported by the findings that:

- diversified firms tend to trade at a discount to a portfolio of comparable focused firms (Berger and Ofek (1995));
- firms that diversified excessively during the 1960s and 1970s were more likely to be acquired and broken up in the subsequent two decades (Mitchell and Lehn (1990)); and that
- when firms diversified into unrelated businesses, the productivity of their existing businesses declined (Schoar (2002)).

Thus, in this view, even though good entrepreneurial ideas might be germinated at these firms, management wisely chooses not to develop them because it would do more harm than good to their core businesses.

This paper is an empirical exploration of the Fairchild and Xerox views of the entrepreneurial spawning process. While we frame the paper as a "horse race" between the two hypotheses, our analysis clearly shows that both types of firms contribute to the creation of venture capital-backed start-ups. Young venture-backed companies in Silicon Valley and along Route 128 in Massachusetts show up as large sources of new venture capital-backed companies, as do large bureaucratic firms. While both Fairchild and Xerox types of spawning occur in practice, we hope to shed light on which view explains differences in the propensity to spawn for a given firm. To analyze these perspectives on spawning, we assemble a database of employees who leave public companies to start venture capital-backed firms during the period 1986 to 1999. From these data, we are able to calculate the spawning levels of public companies. We then relate these spawning levels to firm characteristics in a cross-sectional analysis and examine how these spawning levels change over time for particular firms.

Controlling for firm size, patent portfolio, and industry, we find that the most prolific spawning firms from 1986 to 1999 were public companies located in Silicon Valley and Massachusetts that were once venture capital-backed themselves. These effects are substantial: Being located in Silicon Valley increases the spawning level by almost 38%; companies in Massachusetts have a 24% higher spawning level and companies that were once venture capital-backed have a 23% higher spawning level.

Diversified firms appear to spawn less, not more. Firms focused in one segment have spawning levels that are 19% higher than those operating in multiple segments. Moreover, after controlling for the quantity, quality, and originality of patents that firms have in the areas of principal interest to venture capitalists (computers and communication as well as drugs and medical), the presence of other types of patents in the portfolio (e.g., mechanical patents) tends to reduce a company's spawning level. This result is inconsistent with the notion that more diversified firms spawn more. Our findings appear to be more consistent with the notion that diversified firms are less entrepreneurial and thus less prone to have the sorts of people who would have the inclination, ability, or skills to start new venture capital-backed firms.

The penultimate empirical section of the paper examines how spawning levels change over time for firms. Thus, we construct a panel of annual spawning levels for firms with patents in areas of interest to venture capitalists. When we use firm-fixed effects in our regression analysis, we find that firm spawning levels are lower when a firm's past sales growth is high relative to the firm's mean level of growth. We interpret this finding as indicating that when firms are growing rapidly, employees choose to stay at their firms (and perhaps develop their entrepreneurial ideas internally) because they perceive the rents from doing so to be high. When growth slows, however, employees are more prone to seek entrepreneurial opportunities outside the firm.

One competing interpretation of our findings is that venture capital-backed firms in Silicon Valley and Massachusetts with a history of venture capital backing have high spawning levels not because of entrepreneurial learning, networks, or attributes, but simply because they have technologies and operate in businesses that are of more interest to venture capitalists in the first place (as, e.g., the tabulations in Kortum and Lerner (2000) suggest). While this remains a possible explanation, it is worth noting that we have controlled extensively for patent characteristics (quantity, class, quality, and originality) and for industry. Thus, if high spawners simply function in fields of greater relevance to venture capitalists, they must do so in a way that is neither observable to us nor captured by our patent and industry controls.

As a further check to see that our results are not driven by technology differences, we examine the extent to which venture capital-backed start-ups pursue businesses related to those of the firms from which they are spawned. If technology differences underlie our results, we would expect to see more related spawning from the high spawners. However, this is not what we observe in our empirical analysis. We find instead that firms located in Silicon Valley and Massachusetts with prior venture capital backing spawn *less related* businesses.

Our finding that Xerox-type firms are less likely to spawn is also consistent with the view that they are better at promoting new ventures within the company. However, our finding that these firms are more prone to spawn closely related ventures suggests otherwise. One would think that if Xerox-type firms were better at financing new ventures internally, they would be more prone to keep related ventures in-house.

This paper is closely tied to two strands in the finance literature. First, the roles that venture capital organizations play in business development and the economic impact of their investments have been the subject of increasing academic interest. By exploring the origins of venture-backed firms, this paper contributes to our understanding of this financial intermediary. Second, the effectiveness of established firms, particularly diversified conglomerates, in appropriately identifying and funding additional investment opportunities has attracted considerable scrutiny by financial economists. This paper, with its focus on the circumstances surrounding the departure of executives from publicly traded entities, helps shed light on both of these questions.

The rest of the paper is organized as follows. Section I describes the construction of the data set and summarizes the data. The analysis is presented in Section II. Section III concludes the paper, discusses some implications of our findings, and highlights other research opportunities in this area.

I. Constructing the Data Set

The core data for the analysis come from VentureOne. VentureOne, established in 1987, collects data on firms that have obtained venture capital financing. Firms that have received early-stage financing exclusively from individual investors, federally chartered small business investment companies, and corporate development groups are not included in the database.

The companies are initially identified from a wide variety of sources, including trade publications, company web pages, and telephone contacts with venture investors. VentureOne then collects information about the businesses through interviews with venture capitalists and entrepreneurs. The data collected include the identity of the key founders (the crucial information used here) as well as the industry, strategy, employment, financial history, and revenues of the firm. Data on the firms are updated and validated through monthly contacts with investors and firms.

For the purposes of this analysis, we examine the founders and initial executive officers (henceforth referred to as entrepreneurs) that joined firms listed in the VentureOne database during the period from 1986 to 1999.[2] Typically, the database reports the previous affiliation and title (at the previous employer) of these entrepreneurs, as well as the dates when they joined the firm.[3] In some cases, however, VentureOne did not collect this information. In these cases, we attempt to find this information by examining contemporaneous news stories in LexisNexis, securities filings, and websites of surviving firms.[4] We believe this data-collection procedure may introduce a bias in favor of having more information on successful firms, but it is not apparent to us that it affects our analysis.

Table I summarizes the population of entrepreneurs and their venture capital-backed start-up firms. First, the table presents the number of entrepreneurs that joined new venture capital-backed companies in the VentureOne database by the year that they joined those venture-backed firms, as well the number of new venture capital-backed firms that these entrepreneurs joined in each year. We also list the number of venture capital-backed technology companies. We then present the number of entrepreneurs who held at least one of three key titles in the new company—CEO, president, and chief technical officer (CTO)—as well as the number of entrepreneurs who left firms that were publicly traded. Finally, we report the share of entrepreneurs that were from entities that were publicly traded at the time of their departure.

Two observations should be highlighted from the summary statistics. First, the level of activity has risen over the period we study, reflecting the more general growth of the venture capital industry over these years.[5] The number of entrepreneurs joining venture capital-backed start-ups increases from 483 in 1986 to 1,717 in 1999. Similarly, the number of distinct venture capital-backed firms represented in the sample increases from 218 in 1986 to 799 in 1999. Second, the share of entrepreneurs that emerge from publicly traded firms is significant. The first measure we report calculates the share as a percentage of all entrepreneurs. This measure suggests that there has been an increase of

[2] We did not include events in earlier periods because of concerns about selection biases. VentureOne has gone back to include data on entrepreneurial firms through the early 1980s, but firms that did not survive until 1987 were not added to the database. At the time this study was initiated, the 2000 and 2001 data were substantially less complete than the other years due to lags in identifying and surveying firms.

[3] We code the entrepreneur as being spawned from the most recent company for which he worked, even though he may have a wealth of experience working at other types of companies.

[4] When we were unable to ascertain the year in which the individual joined the firm, we used the year in which the firm was formed, which was the modal answer in cases where we had complete data. This approach does introduce some empirical difficulties, as we discuss below.

[5] The reader may be puzzled that the volume of spawned venture capital-backed start-ups falls in 1999, a record year for venture capital activity. This decline occurs because the years reported are those where the entrepreneurs joined the new firms, not the year of the first venture capital financing. Thus, even though many more entrepreneurs may have joined start-ups in 1999, it is likely that a smaller percentage of them were later funded by venture capital because of the plunge in the Nasdaq in April 2000 and the subsequent drop in overall venture capital funding.

Table I

Summary of Entrepreneurs

The sample is based on VentureOne's database of 15,297 founders of 5,112 venture capital-backed start-ups who received venture capital financings from 1986 to 1999. The previous employment history of the founders is tabulated. Public companies are those identified from COMPUSTAT. The fourth column lists the number of founders who are the CEO, president, or chief technology officer of the start-up. The fifth column lists the number of founders whose most recent employer was a public company.

Year	Number of Entrepreneurs	Number of Start-ups	Number of Technology Start-ups	CEO/ Pres/ CTO	Number of Entrepreneurs from Public Companies	Fraction from Public Companies (%)	Fraction from Public Companies When We Have Previous Company Identified (%)
1986	483	221	144	268	145	30.0	45.9
1987	628	260	171	325	196	31.2	43.6
1988	694	267	172	359	229	33.0	44.2
1989	721	292	176	392	246	34.1	43.6
1990	843	333	214	463	295	35.0	44.3
1991	840	345	222	484	307	36.5	45.1
1992	1,065	408	237	567	342	32.1	41.4
1993	1,016	384	221	606	380	37.4	46.3
1994	1,172	446	253	747	368	31.4	41.3
1995	1,290	527	257	906	417	32.3	41.4
1996	1,623	680	372	1,236	599	36.9	44.6
1997	1,448	669	361	1,109	535	36.9	42.6
1998	1,747	809	365	1,376	692	39.6	45.0
1999	1,717	804	232	1,396	717	41.8	46.5

about 40% over this period in the share of entrepreneurs coming from public companies (from 30% to 42% of the entire sample of entrepreneurs). There are many entrepreneurs, however, for whom the database reports no prior work history. If one excludes these entrepreneurs from the calculation, the share of entrepreneurs coming from public companies appears to be more stable, averaging approximately 45% per year. The difference in these findings is probably attributable to the more complete reporting of prior work histories in later years.[6]

The data on entrepreneurs are linked to information on the companies that spawned them. In particular, we determine whether the entrepreneur had previously been employed at a publicly traded firm in the United States, and, if so, we link it to the appropriate firm in the COMPUSTAT and Center for Research into Securities Prices (CRSP) databases. We also identify the spawning firm's patents (and their characteristics) using the National Bureau of Economic Research's (NBER) patent citations data file (summarized in Hall, Jaffe, and Trajtenberg (2001)). This database links patent data from the U.S. Patent Office to COMPUSTAT (as it was comprised in 1989). We add links for companies listed in COMPUSTAT after 1989.[7]

Table II lists the firms and industries that were most active in spawning new firms. Panel A lists the 48 publicly traded corporations that spawned 10 or more entrepreneurial teams during the sample period. (Multiple individuals departing to establish a firm are regarded as a single team.) Panel B describes the top 3-digit standard industrial classification (SIC) codes in which the most spawners operated. (Each firm is assigned to one 3-digit SIC code, based on the primary industry assigned in COMPUSTAT.) The dominant importance of firms in the software, computer and office equipment, and drug industries is apparent. The concentration of entrepreneurs spawned from public firms in these industries closely mirrors the overall investment pattern of the venture capital industry. It is not surprising that the venture capitalists would finance entrepreneurs with relevant technology experience.

Panel C of Table II highlights the breakdown of the annual spawning activity by the size of the parent firm, as measured by annual employment between 1986 and 1999. (As we will discuss below, in some cases we cannot determine the year in which the spawning occurred, so not all observations can be used.) We break down the firms into the four roughly equally sized clusters (by number of entities): less than 100 employees, between 100 and 1,000 employees, between

[6] Kaplan, Sensoy, and Strömberg (2002) show that the VentureOne database does not have any bias in regard to location or round size. They find that there is a slight tendency for VentureOne to pick up more highly valued rounds. This slight bias, however, does not affect our results because our unit of analysis is the firms that spawn new companies. There is no reason to believe that sampling on slightly more valuable rounds would introduce a bias in our sample of entrepreneurs.

[7] Because there are a large number of companies listed in the patent database, it was not feasible to scan the entire database for possible links to COMPUSTAT. Thus, we listed all companies in the patent database with at least two patents in the computers and communication and medical and drugs patent categories and narrowed our search of public companies to this subset of patent holders.

Table II

Summary of Information on Previous Employer of Founders

The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999. A spawned entrepreneur is an employee who leaves a public company to start a venture capital-backed firm. Data on founders come from the VentureOne database of 15,297 founders of 5,112 venture capital-backed start-ups during the period 1986 to 1999. Panel A lists all public companies that spawn at least 10 entrepreneurial teams during the sample period, 1986 to 1999, and the number of entrepreneurial teams they spawn during the sample period. (Multiple individuals departing to a single firm are regarded as a single entrepreneurial team.) Panel B lists all industries in which public companies spawn at least 20 entrepreneurial teams in total and the number they spawn. Panel C summarizes the distribution of firm size and spawning activity.

Panel A: Top Public Spawning Companies

Company	Number of Spawned Entrepreneurial Teams	Company	Number of Spawned Entrepreneurial Teams
IBM	70	Nortel Networks	17
AT&T	60	Unisys	17
Sun Microsystems	55	National Semiconductor	17
Apple Computer	48	Advanced Micro Devices	16
Hewlett-Packard	46	Mentor Graphics	15
Oracle	41	Cirrus Logic	14
General Electric	37	Genentech	14
Microsoft	30	Bristol Myers Squibb	14
Xerox	29	Raychem	14
Baxter	29	Dun & Bradstreet	14
Intel	28	SmithKline Beecham	13
Disney	28	MCI	13
Silicon Graphics	27	Pfizer	13
Lotus Development Corporation	26	Texas Instruments	13
Motorola	25	Legent	12
DEC	24	Tandem Computer	12
Cadence Design Systems	21	Bank of America	11
Johnson & Johnson	21	PeopleSoft	11
Verizon	19	Morgan Stanley	11
Novell	18	Adaptec	11

Panel B: Top 3-Digit Industries for Spawners

Industry	Number of Spawned Entrepreneurial Teams
Computer programming and data processing	1,009
Computer and office equipment	588
Drugs	348
Communication equipment	212
Surgical, medical, and dental instruments	204
Electronic components and accessories	185
Telephone communications	178
Laboratory, analytical, and optical equipment	83
Security brokers, dealers, and flotation	61
Radio and television broadcasting stations	52
Commercial banks	50
Non-store retailers	30
Special industry machinery, except metalworking	24

(*continued*)

Table II—*Continued*

Panel C: Distribution of Spawning Firms by Employment

Employment Range	Share of All Firms (%)	Share of Employment (%)	Share of Firms Spawned (%)	Annual Spawning/ Million Employees
100 or less	22.0	0.1	0.4	32.7
101 to 1,000	28.9	0.7	1.3	7.8
1,001 to 10,000	24.9	5.9	6.3	4.7
10,001 to 100,000	21.7	59.5	54.6	4.1
100,001 or more	2.4	33.8	37.4	4.9

1,000 and 10,000, and above 10,000. Because the bulk of the economic activity is in the final group, we divide this category again. The tabulation highlights the fact that while the largest companies spawn the most new firms, the larger firms are actually less likely to spawn firms than their share of employment (or, for that matter, assets or revenues) would suggest. The annual spawning rate of those firms below the median size is considerably higher than that of the other firms in the sample.

Table III compares spawning firms to nonspawning firms. We take averages for each company that ever spawned a venture capital-backed start-up in the VentureOne database during these years, that is, those that spawned at least one entrepreneur over the time period. We contrast these firms with those that spawned no venture capital-backed firms. For the purposes of interpreting our later results, we report summary data only on those firms that end up in our basic regression analysis.

The tabulation reveals that spawning firms tend to be significantly larger than nonspawners. For instance, the median spawning firm has 60% higher sales, 90% greater assets, and 170% more employees. Tobin's Q is calculated as the ratio of the market value of the firm to the book value of its assets, following the procedure delineated in Kaplan and Zingales (1997). Because the distribution of Tobin's Q has a dramatic rightward skew, we report winsorized versions of this measure, cutting off the distribution at a Q of 10, roughly corresponding to the 99th percentile. The mean Q of spawning companies (2.75) is somewhat higher than the mean Q of nonspawning firms (2.54). The difference in the medians is much larger: 2.18 versus 1.71. The average EBITDA to assets ratio is not appreciably different across the two subsamples, but sales growth is considerably higher among the spawning firms.[8]

In addition to looking at differences in the financial performance of spawning and nonspawning firms, we also tabulate whether the headquarters of these firms are in Silicon Valley or Massachusetts. Prior venture capital backing

[8] These measures are also winsorized. In the case of EBITDA to assets, we cut off any ratios below −0.5 and above 0.5 and in the case of sales growth we cut off any rates above 10.

Table III

Characteristics of Public Spawners versus Nonspawners

The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999. Spawners are identified as those public companies in which at least one employee left to start a venture capital-backed firm. Data on founders come from the VentureOne database of 15,297 founders of 5,112 venture capital-backed start-ups during the period 1986 to 1999. The table compares the characteristics of public companies that spawn at least one entrepreneur during the sample period 1986 to 1999 (the first three columns) to the characteristics of public companies that never spawn during the sample period (the second three columns). All dollar figures are in millions of 1999 dollars. Patent category 2 refers to computer and communication patents as classified in the NBER Patent Citations Data File and category 3 refers to medical and drug patents. The differences in the means are all statistically significant based on heteroskedasticity-consistent t-statistics that adjust for nonindependence of observations within the same 2-digit SIC code.

	Spawners			Nonspawners		
	Median	Mean	Observations	Median	Mean	Observations
Sales ($MMs)	$185.2	$3,428.6	515	$116.1	$1,343.3	855
Assets ($MMs)	$191.7	$4,949.1	515	$100.5	$1,732.6	855
Employees (000s)	23.1	44.2	515	0.8	8.0	855
Winsorized sales growth[a]	19.3%	52.6%	515	11.2%	37.6%	855
Winsorized Tobin's Q[a]	2.18	2.75	515	1.71	2.54	855
Winsorized EBITDA/assets[a]	0.111	0.058	515	0.107	0.054	855
Venture capital-backed		35.5%	515		12.2%	855
Silicon Valley		19.8%	515		5.9%	855
Massachusetts		9.9%	515		5.9%	855
Number of spawned entrepreneurs	2	4.07	515			
Number of patents in category 2	4	137.5	515	2	15.9	855
Number of patents in category 3	0	51.2	515	0	10.8	855
Patent quality	0.618	1.336	515	−0.922	−0.606	855
Patent originality	0.019	0.019	515	0.062	0.059	855

[a]Observations with greater than the 99th percentile are coded as being at this level.

is determined by linking the companies to the Venture Economics database of venture capital financings (discussed in Gompers and Lerner (1999)), and then supplemented with the annual listing of venture capital-backed IPOs in *Venture Capital Journal*. Following Saxenian (1994), we define Silicon Valley as California's Alameda, San Mateo, and Santa Clara counties. Although the hub of start-up activity in Massachusetts is around Route 128 (Middlesex County), the state is small enough that it is not meaningful to make distinctions among the counties of Massachusetts. We determine the headquarters' location from COMPUSTAT. Spawning firms are much more likely to have been venture capital-backed themselves (35.5% vs. 12.2%) and to be located in the hubs of venture capital activity—Silicon Valley and Massachusetts.

The table also lists information on the degree of focus of the spawning and nonspawning firms. We consider a firm focused if it reports just one industry segment in its filings with the Securities and Exchange Commission.[9] Spawning firms tend to be more focused even though they are substantially larger.

Not surprisingly, spawning firms have considerably more patents over the period from 1980 to 1999, particularly in patent classes that are most relevant to venture capital, that is, patents with a primary assignment to category 2, computers and communications, or category 3, drugs and medical, using the classification scheme in the NBER data file.

Finally, the table reports information on the average quality and originality of patents in categories 2 and 3 for these companies. The standard measure of patent quality (see the extended discussion in Jaffe and Trajtenberg (2002)) is the number of citations the patent receives. We use this citation measure of quality, adjusting for the year in which the patent was granted and the subcategory of the patent.[10] Thus, our quality measure is the firm-fixed effect in a regression of a patent's citations on a set of dummy variables for the year in which the patent was granted and the patent subcategory. The table indicates that the average patent quality of spawning firms is higher than that of nonspawning firms.

Recent research (summarized in Jaffe and Trajtenberg (2002)) has highlighted the importance of the measure of patent originality. A patent is considered more original if it cites patents across more patent categories, as it is more likely to synthesize knowledge across a variety of disciplines. We use this measure reported in the NBER patent citations data file, again adjusting for the granting year of the patent and the patent's subcategory. The table shows

[9] There are a number of limitations on this focus measure. One is that firms have discretion in what businesses they choose to lump together into a business segment. Thus, some single-segment firms that pool a number of businesses into one segment may be no more focused than a multisegment firm that breaks them out. Another limitation is that some of the multiple segment firms may have quite related businesses across different segments. Our measure takes no account of those relationships. Despite this measurement error, it is likely that, on average, the firms we categorize as focused are indeed more focused than the other firms in the sample.

[10] The NBER database includes four subcategories for computers and communications: communications, computer hardware and software, computer peripherals, and information storage. There are four subcategories for drugs and medical: drugs, surgery and medical instruments, biotechnology, and miscellaneous.

that the average originality of patents held by spawning firms is lower than that of nonspawning firms.

II. Analysis

We present the results here in five subsections. We start in Section II.A by analyzing the factors that affect the total number of venture capital-backed start-ups that public companies spawn over the entire sample period, 1986 to 1999. In Sections II.B and II.C, we examine the extensive and intensive margins of spawning—that is, the factors that determine whether a firm spawns at all and the factors that determine how much spawning a firm undertakes conditional on spawning at least one firm. We then examine in Section II.D whether the factors that explain overall spawning levels explain spawning levels on a yearly basis. In this section, we also look at the annual spawning levels in a model with firm-fixed effects. Thus, in this part of the paper, we are able to examine the time-varying characteristics that affect whether a firm's spawning level is above or below its own mean. In Section II.E, we examine the extent to which the activities of the spawned firms are related to their parents.

A. The Determinants of Total Spawning

In this section, we analyze the factors that affect the total number of venture capital-backed companies spawned by public companies during the sample period 1986 to 1999. Our methodology follows the productivity literature, which frequently estimates production functions that seek to explain how an activity of interest (e.g., R&D spending or patenting) varies with firm size and other characteristics. A critical concern in this literature is frequently the elasticity of innovation with respect to firm characteristics: for instance, does doubling firm size lead to doubling R&D spending, or is this elasticity less or greater than one?

One issue that we face from the outset is that some firms have very little spawning activity simply because they specialize in areas that are of little interest to venture capitalists. Indeed, historically, more than 80% of venture capital disbursements have gone to firms in the information technology and health-related fields. Thus, for the bulk of the analysis, we restrict our analysis to firms that were awarded at least one patent between 1981 and 1999 in NBER patent categories 2 (computer and communications) or 3 (drugs and medicine), which correspond to areas of greatest interest to venture capitalists.

Our dependent variable is the logarithm of the number of venture capital-backed start-ups that the firm spawns over the sample period (plus the number one to avoid dropping nonspawning firms). When more than one person leaves a given company in a given year to form a particular firm, we still count it as one firm that was spawned. In some of the analyses, we look only at spawning of start-ups in technology-intensive businesses for which the patents in categories 2 and 3 are most relevant. As shown in Table I, these spawned firms account for roughly two-thirds of the companies spawned in a given year.

We start by looking at overall spawning because of our inability to identify the spawning date with certainty for every venture capital-backed company. In many cases, VentureOne does not report the date on which the entrepreneur joined the start-up. In these cases, we tried to fill in this information from publicly available information, but in many of them, we were unsuccessful. When we could not find the information from other sources, we used the founding date of the start-up. There are, however, a number of cases in which the founding date of the company precedes the founding date of the public company, indicating that the entrepreneur most likely joined at a later time. These observations are dropped from the analysis when annual spawning levels are analyzed. This tends to disproportionately reduce the measured spawning levels of young public companies. Of course, looking at overall spawning levels has its own limitations, the most important of which is that it does not allow us to examine the time dynamics of spawning. Since there is no perfect solution to this problem, we analyze the determinants of total spawning levels here and analyze annual spawning levels in Section II.D below.

The first column of Table IV reports the results of a cross-sectional regression in which the dependent variable is the log of a firm's total spawning. The mean of this variable is 0.482, indicating that the average firm spawns 0.619 firms between 1986 and 1999. The regressors in this analysis are: (1) the log of the total number of patents the firm was granted between 1981 and 1999 in each of the six NBER patent categories (as described in Hall et al. (2001)); (2) the mean of logarithm of the firm's assets over the sample period expressed in 1996 dollars; (3) the mean ratio of EBITDA to assets; (4) the mean annual growth of real sales; (5) the mean of annual Q; (6) a dummy variable that equals one if the firm was venture capital-backed; (7) separate Silicon Valley and Massachusetts dummies; (8) the mean of the firm's focus dummy; (9) the quality of patents in categories 2 and 3; and (10) the originality of the patents in categories 2 and 3. Because the firms are in the sample for different numbers of years, we also include a set of dummy variables for each year the firm is in the sample. The t-statistics are based on heteroskedasticity-adjusted standard errors that allow for nonindependence of observations across firms within the same 2-digit SIC code.

Not surprisingly, the coefficients of the patent quantities in categories 2 and 3 are positive and highly statistically significant. The coefficient indicates that the elasticity of spawning with respect to patenting in category 2 is 0.220 and that the elasticity in category 3 is 0.144. It is noteworthy also that this elasticity is less than one; doubling a company's patents generates significantly less than twice as many spawned entities. There may be several explanations for this finding. First, not all businesses are based on patents and technological know-how; patents may be irrelevant for these spawned entities. Second, many patents may have no immediate practical business value. If larger firms with more patents are more likely to have such patents (perhaps because they have internal patent departments that reduce the cost of applying for patent awards, and thus make it worthwhile to apply for more marginal awards), the incremental impact of a patent on spawning activity could be lower. A third

Table IV

Regression Analyses of Spawning Levels

The table presents regression results for the cumulative number of spawned entrepreneurs for each firm in our sample. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the regressions is the natural logarithm of the cumulative number of venture capital-backed entrepreneurs spawned over the whole sample period. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous three years winsorized at the 99th percentile; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; a dummy variable indicating whether the firm was backed by venture capitalists; dummy variables indicating if the firm was located in Silicon Valley or Massachusetts; measures for the firm's patent quality and originality; the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies for every year that the firm is in the sample, though the coefficients are not shown; some include industry-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations within the same 2-digit SIC code.

	Dependent Variable: Log of Number of Entrepreneurs Spawned			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Log of chemical patents	−0.0191	−0.0146	−0.0093	−0.0067
	[−1.18]	[−1.08]	[−0.51]	[−0.39]
Log of computer and communications patents	0.2203	0.1958	0.1864	0.1707
	[6.75]	[6.34]	[8.60]	[8.35]
Log of drugs and medical patents	0.1443	0.1449	0.1384	0.1431
	[8.99]	[9.99]	[6.74]	[7.27]
Log of electrical and electronic patents	−0.0259	0.0012	0.0008	0.0221
	[−0.82]	[0.05]	[0.04]	[1.17]
Log of mechanical patents	−0.0376	−0.0457	−0.0673	−0.0752
	[−2.45]	[−2.81]	[−3.12]	[−3.66]
Log of other patents	−0.0614	−0.0616	−0.0556	−0.0579
	[−4.19]	[−5.23]	[−2.50]	[−2.81]
Log of real assets	0.1250	0.0897	0.1504	0.1143
	[7.77]	[7.40]	[9.11]	[7.26]
Mean winsorized EBITDA/assets[a]	−0.1380	−0.0891	−0.3679	−0.2788
	[−1.42]	[−1.23]	[−2.89]	[−2.27]
Mean winsorized sales growth over previous year[a]	0.0122	0.0062	0.0131	0.0082
	[0.88]	[0.42]	[0.73]	[0.42]
Mean winsorized Tobin's Q[a]	0.0219	0.0157	0.0149	0.0115
	[3.70]	[3.70]	[1.45]	[1.18]
Venture capital-backed	0.2335	0.2135	0.1895	0.1728
	[6.11]	[9.61]	[3.89]	[3.56]
Silicon Valley-based	0.3772	0.3875	0.3461	0.3606
	[6.93]	[7.08]	[5.17]	[5.43]
Massachusetts-based	0.2355	0.2066	0.2013	0.1793
	[3.62]	[2.96]	[3.26]	[2.91]

(*continued*)

Table IV—*Continued*

	Dependent Variable: Log of Number of Entrepreneurs Spawned			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Focused firm	0.1952	0.1484	0.1893	0.1438
	[2.69]	[2.64]	[3.42]	[2.76]
Log of firm age	−0.0575	−0.0603	−0.0488	−0.0552
	[−2.36]	[−2.60]	[−1.96]	[−2.38]
Patent quality	0.0061	0.0066	0.0043	0.0049
	[4.74]	[4.23]	[1.73]	[2.08]
Patent originality	−0.0841	0.0257	−0.1473	−0.0279
	[−1.05]	[0.49]	[−1.81]	[−0.37]
Constant	−0.8499	−0.7153	−0.9714	−0.8285
	[−6.21]	[−6.25]	[−9.48]	[−8.35]
Number of observations	1,370	1,370	1,370	1,370
Adjusted R^2	0.418	0.403	0.433	0.400
Industry-fixed effects	No	No	Yes	Yes

[a]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

possibility is that some patenting may be an attempt to limit the extent to which employees take their ideas and start new ventures. Finally, to the extent that we have included other measures of size, such as the logarithm of real assets, these variables may be picking up some of the effect of an increase in patenting.

Interestingly, the coefficients on the other four patent categories are all negative and, in the case of mechanical patents (category 5) and other patents (category 6), they are statistically significant. This finding suggests that having research activities outside of the main venture capital-related areas reduces the level of spawning. This is not consistent with the Xerox view that spawning is a consequence of corporate bureaucracy. It is, however, consistent with the Fairchild view to the extent that firms operating in multiple areas of research tend to be less entrepreneurial in style and attract a less entrepreneurial type of employee. We discuss this and related findings later in this section.

Table IV also indicates that firms with more assets spawn more firms, which is not surprising given that the dependent variable is not size-adjusted. The fact that larger firms spawn more reflects that there are more people and technologies that potentially could generate the ideas for new ventures here. It is important to note, however, that the elasticity of spawning with firm size is considerably less than one. For example, doubling the assets and the number of patents held by a firm specializing in information technology leads to only a 34.5% (0.220 + 0.125) increase in the predicted number of firms spawned.

There is no statistically significant link between spawning and EBITDA over assets, nor with one-year real sales growth. High Q firms do, however, spawn more. There are many potential explanations for this finding. One plausible explanation is that firms have high Q because they are expected to develop new businesses. The ideas for these new businesses are generated by the firm's employees and some of them may choose to develop the ideas on the outside, backed by venture capital. Alternatively, high Q firms may have better networks with customers and suppliers that both enhance firm value and ease starting new ventures.

The coefficient of the venture capital dummy is positive, large, and highly statistically significant. The estimate of 0.233 indicates that, all else being equal, public companies that were once venture capital-backed spawn 23.3% more firms than those that were not venture capital-backed. The coefficient of the Silicon Valley dummy indicates that public companies based in Silicon Valley spawn 37.7% more firms than those based outside the two hubs of venture capital activity. The coefficient estimate on the Massachusetts dummy is also large and statistically significant; while it is smaller than the effect of being in Silicon Valley, the effect is comparable in size to that of being venture capital-backed.

The result that venture capital-backed firms spawn more is consistent with the Fairchild view of spawning. In this view, employees of venture capital-backed firms learn how to be entrepreneurs through the experience of working in an entrepreneurial environment. They may also have greater exposure to the network of suppliers of goods, capital, and labor, as well as customers. Furthermore, employees who join venture capital-backed firms may be less risk averse, and thus more willing to accept the risks associated with starting a new company. While it is difficult to determine the precise mechanism through which employment at a venture capital-backed firm affects the amount of spawning, the effect is quite strong in the data. The finding does not appear to be consistent with the alternative Xerox view of spawning.

The positive effect of being located in Silicon Valley and Massachusetts is also consistent with the Fairchild view. In both regions, employees have a closer connection to a network of suppliers of goods, capital, and labor that is critical to the creation of a new enterprise. Saxenian (1994) argues that being located in a region with other small entrepreneurial firms makes it easier to find companies that are willing to supply critical inputs. She argues that this effect is stronger in Silicon Valley than in Massachusetts because the latter region tends to have larger, more vertically integrated firms. Although we estimate a larger effect in Silicon Valley than in Massachusetts, it would be a stretch to say that we have confirmation of Saxenian's claim.

We also find that a firm's average level of focus is positively related to the extent of its spawning. The estimated effect is also quite large. A firm that is focused throughout the sample period spawns 20% more than a company that is diversified throughout. This finding appears at odds with the view that spawning is a response to bureaucratic rigidities in large, technology-intensive firms. The result appears more consistent with the Fairchild view.

The regression results also indicate that older public companies spawn fewer venture capital-backed start-ups.[11] The estimated elasticity of 5.8% is small.

[11] This finding is consistent with Dobrev and Barnett's (2002) analysis of the career paths of business school graduates.

Given the imprecision with which we measure firm age, these results need to be interpreted with some caution.

Finally, the regression includes measures of patent quality and originality. Firms with higher quality patents in categories 2 and 3 appear to spawn more, while those with lower average originality appear to spawn less. The coefficient of patent quality is statistically significant, while the coefficient of patent originality is not. An increase from the 25th percentile of quality to the 75th percentile—an increase of 6.3 adjusted citations—leads to an increase of 2.8% in the level of spawning, a small effect. Like the age effect, the estimated effect of patent quality is rather unimpressive.

The second set of regressions in Table IV uses spawning in technology industries as the dependent variable. We find the same basic patterns of results here as we did in the regression with overall spawning. The last two columns repeat the first two but add industry dummies for 2-digit SIC codes. The key findings are unaffected: The coefficients of the venture capital, Silicon Valley, and Massachusetts dummies and the coefficient of average focus all remain positive and statistically significant. The magnitudes of the coefficients also change very little. Mean Q, age, and patent quality are no longer statistically significant, though their magnitudes change very little.

In Table V, we repeat the analyses in Table IV, exploring the impact of alternative specifications. One possibility is that many of the entrepreneurs in our sample had little to do with the development of the companies. Many executives may be lured to start-up firms primarily not for their ability to create a technology or service, but for their ability to sell a technology or service. Thus, many of the parent firms that seemingly spawned an idea may have had contributed executives who made little contribution to the actual establishment of the start-up firms.

To address this concern, we repeat the analysis in the first column of Table IV, but confine the analysis to individuals who held scientific and technical titles at their old or new firms[12] or else were the senior leadership of the new firm (holding the title of chairman, chief executive officer, or president). We eliminate all other officers from the tabulations.

These results are presented in the first column of Table V. The age of the spawning firm is no longer statistically significantly at the 5% confidence level. Otherwise, the results are little changed. The results are similarly robust when we confine the analysis to individuals who held scientific and technical titles at their previous or new firms.

A second concern is that the dynamics of spawning firms in the two most common classes of firms—information technology and life sciences—may be different. In the second and third columns of Table V, we repeat the analysis shown in the first column of Table IV, but now use as a dependent variable either the count of the spawning of information technology or life sciences firms. In each case, we restrict the sample to those potential spawned firms that have one patent in the relevant cluster of patent classes.

[12] We define these individuals as those who held the title of chief technology officer, engineer, or scientist in either the new firm or else in one of their previous two places of employment.

Table V

Robustness Checks of Regression Analyses of Spawning Levels

The table presents additional regression results. The sample is derived from public companies listed in COMPUTSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the first regression is the natural logarithm of the cumulative number of venture capital-backed entrepreneurs who held scientific and technical positions in their previous or new firms or else were the senior leadership of the new firm (holding the title of chairman, chief executive officer, or president) spawned over the whole sample period; in the second and third regressions, it is the natural logarithm of the cumulative number of entrepreneurs who founded information technology and life sciences firms (based on the VentureOne industry classification scheme); and in the final regression, it is (unlogged) ratio of the number of companies spawned over the average level of employment for this period. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous 3 years winsorized at the 99th percentile; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; a dummy variable indicating whether the firm was backed by venture capitalists; dummy variables indicating if the firm was located in Silicon Valley or Massachusetts; measures for the firm's patent quality and originality; the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. In the fourth regression, the ratio of the patent count variables (now in thousands) and assets to the average number of employees (in thousands) are used (not logged). All regressions include year dummies for every year that the firm is in the sample, though the coefficients are not shown. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations within the same 2-digit SIC code.

	Dependent Variable: Number of Entrepreneurs Spawned			
Independent Variables	Who Are Scientists, Engineers, or Key Leaders (log) (1)	Who Founded I.T. Firms (log) (2)	Who Founded Life Sciences Firms (log) (3)	Normalized by Employees (4)
Log of chemical patents[a]	−0.0240	−0.0087	−0.0054	0.0029
	[−1.44]	[−0.46]	[−0.69]	[0.03]
Log of computer and communications patents[a]	0.1953	0.2169	0.0204	−0.0311
	[6.41]	[9.60]	[1.62]	[−1.73]
Log of drugs and medical patents[a]	0.1268	−0.0144	0.1669	−0.0704
	[9.62]	[−0.83]	[9.62]	[−1.66]
Log of electrical and electronic patents[a]	−0.0309	−0.0242	−0.0056	0.0880
	[−1.05]	[−1.00]	[−0.26]	[1.44]
Log of mechanical patents[a]	−0.0147	−0.0332	−0.0163	−0.0498
	[−0.76]	[−1.56]	[−0.61]	[−0.53]
Log of other patents[a]	−0.0513	−0.0391	−0.0294	−0.3275
	[−3.24]	[−1.86]	[−1.87]	[−1.55]
Log of real assets[a]	0.1119	0.0885	0.0669	0.0112
	[7.03]	[5.06]	[3.50]	[4.47]
Mean winsorized EBITDA/assets[b]	−0.0453	0.3604	−0.2892	−0.0485
	[−0.46]	[2.46]	[−4.67]	[−1.68]
Mean winsorized sales growth over previous year[b]	0.0190	−0.0087	0.0289	−0.0017
	[1.35]	[−0.57]	[4.86]	[−0.57]

(*continued*)

Table V—*Continued*

Independent Variables	Dependent Variable: Number of Entrepreneurs Spawned: Who Are Scientists, Engineers, or Key Leaders (log) (1)	Who Founded I.T. Firms (log) (2)	Who Founded Life Sciences Firms (log) (3)	Normalized by Employees (4)
Mean winsorized Tobin's Q^b	0.0260	0.0184	0.0125	0.0048
	[3.89]	[1.67]	[2.11]	[4.77]
Venture capital-backed	0.1940	0.2297	0.0891	0.0310
	[4.26]	[5.66]	[3.10]	[2.35]
Silicon Valley-based	0.2668	0.3805	0.2112	0.0543
	[6.32]	[5.19]	[3.61]	[4.25]
Massachusetts-based	0.1807	0.2703	0.0462	0.0405
	[3.18]	[3.21]	[1.18]	[3.36]
Focused firm	0.2161	0.1197	0.0820	0.0657
	[3.51]	[3.11]	[2.83]	[6.18]
Log of firm age	−0.0297	−0.0350	−0.0716	−0.0117
	[−1.79]	[−1.62]	[−2.40]	[−3.34]
Patent quality	0.0046	0.0083	0.0041	0.0013
	[2.96]	[4.47]	[2.97]	[3.90]
Patent originality	−0.0806	0.0030	0.1084	−0.0194
	[−1.31]	[0.03]	[2.82]	[−0.90]
Constant	−0.8887	−0.7293	−0.5875	−0.0985
	[−6.18]	[−7.13]	[−5.87]	[−5.06]
Number of observations	1,370	818	590	1,337
Adjusted R^2	0.400	0.463	0.351	0.164
Industry-fixed effects	No	No	No	No

[a]These variables are normalized by assets in the regression in the final column, as is the dependent variable.
[b]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

The results show that the dynamics of spawning in these industries are quite similar to that in the sample as a whole. Not surprising, the influence of patent awards in the relevant technology class is significant both statistically and economically. A more interesting difference lies in the impact of profitability. In contrast to the sample as a whole, the more profitable information technology firms are the most prolific spawners. The successful spawning firms in the life sciences industry are more likely to have original patents (perhaps reflecting the importance of intellectual property in this industry) and are less likely to be located in Massachusetts.

Another worry has to do with the specification. In the reported regressions, we have employed a production function framework, examining how the number of firms spawned varies with a variety of measures, including firm size. While this specification is by far the most commonly employed one in the literature (e.g., see Griliches (2000)), it is certainly not the only empirical approach we can adopt. A natural question is whether the results are robust to alternative specifications.

The fourth column of Table V presents one such alternative specification, in which the dependent variable is the (not logged) ratio of companies spawned, normalized by the average number of employees that the firm had while it was in the sample. Similarly, we use the count of patents normalized by the number of employees as independent variables. We also normalize assets by employees to measure the asset intensity of the firm.

Some differences appear in this specification. The patent awards measures—which no longer partially capture the scale of the firm—are no longer statistically significant. But most of the other results are largely as before. Younger firms with a larger assets-to-employees ratio, financed by venture capital, based in Silicon Valley and Massachusetts, strongly focused on a single product line, and with higher quality patents, are more likely to spawn new firms. This specification—and other similar unreported regressions—help address concerns that the results may be an artifact of the failure to adjust for firm size.[13]

In unreported regressions, we address additional concerns. One major issue is the influence of repeat entrepreneurs. "Serial entrepreneurs," who work at multiple entrepreneurial firms, are said to be important in many industries. It is reasonable to worry that serial entrepreneurs drive our results that firms based in Silicon Valley and Massachusetts and backed by venture capitalists spawn more. That is, these firms may not teach their employees how to be entrepreneurs or expose them to networks, or even select for entrepreneurial types. Instead, firms with these characteristics may tend to be younger and more likely to have been founded in the recent past by entrepreneurs. These entrepreneurs may then leave to start other firms, leading to the appearance that these firms are more prolific spawners.

We thus repeat the analysis, dropping cases where an entrepreneur had been involved with a previous venture-backed firm. To do this, we create an identifier for each entrepreneur, researching the sources noted above to determine whether a Jim Joyce and a James Joyce in the VentureOne database are really the same person. In all, the elimination of repeat entrepreneurs leads to the elimination of 9.7% of the observations, where the entrepreneur was involved as a founder or key officer in a previous venture-backed firm. Of the repeat entrepreneurs in the sample, 83% are involved with two firms, 13% with three, 3% with four, and less than 1% with five or more firms.

The deletions have little impact on the results. Neither the magnitude nor the statistical significance of the key results presented in Table IV changes. Similarly, when we repeat the analyses reported in later tables, the deletion of the repeat entrepreneurs has little impact.

[13] For instance, we repeat the analysis, adding the reciprocal of employment as an independent variable (following the approach recommended by Griliches (2000) for adding scale effects in such specifications). The coefficient proves to be both statistically and economically insignificant.

B. The Characteristics of Firms That Spawn

In the sample of 1,370 companies that patent in categories 2 and 3, 515 companies spawn at least one venture capital-backed firm and 855 spawn none. What are the factors that determine whether a firm spawns at least one firm? To address this question, we report the results of regressing a dummy variable that takes the value one if the firm spawns at all on the same set of regressors as those reported in Table IV. Although we report the ordinary least squares estimates in Table VI, results using logit and probit specifications are substantively similar.

Not surprisingly, firms with more patents in categories 2 and 3 are more likely to spawn a venture capital-backed start-up. A firm with only one patent in category 2 (the 25th percentile of patent quantity) has a 33.5% chance of spawning a venture capital-backed start-up, whereas a firm with nine patents in category 2 (the 75th percentile) has a 54.6% chance of spawning a venture capital-backed start-up. The estimated effect for patents in category 3 is similar in magnitude. Patenting in the other patent categories—particularly in categories 5 and 6—tends to reduce the probability of spawning.

The estimated effects of the critical variables of interest—prior venture capital backing, location, and focus—are all large and statistically significant. The predicted probability of spawning any start-up is 20.2% higher for venture capital-backed public companies than for firms that were not venture capital-backed. The empirical model predicts that nonventure capital-backed public firms have a 33.0% probability of spawning at least one company, while a venture capital-backed public company has a 53.1% chance of spawning such a firm. The estimated effects are similar in magnitude for firms located in Silicon Valley and Massachusetts. Firms located outside of either have a 34.7% chance of spawning at least one start-up, while a public company located in Silicon Valley has a 51.2% chance of spawning a start-up and one located in Massachusetts has a 48.4% chance of spawning a start-up.

The estimated effect of the focus variable is somewhat smaller than those of location and prior venture capital backing. A firm that is focused throughout the sample period has a 51.8% chance of spawning at least one start-up, while a firm that was diversified throughout the sample has a 43.4% chance of spawning a start-up. In interpreting the magnitude of the focus coefficient, however, one has to keep in mind that the regression also includes the number of patents outside of categories 2 and 3, which also measures the degree of focus. Indeed, if one excludes the quantity of patents outside of categories 2 and 3, the estimated coefficient of average focus doubles in magnitude and is highly statistically significant in all specifications.

With respect to patent characteristics, patent quality appears to be significantly and positively related to spawning at least one company, while the effect of originality is negative albeit statistically insignificant.

The second column of Table VI repeats this specification for the spawning of technology-intensive businesses. The results are essentially unchanged. The last two columns add 2-digit SIC code industry dummies. The estimated effects

Table VI

Regression Analyses of Likelihood of Doing Any Spawning

The table presents regressions of the probability of a sample firm having any spawning activity. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the regressions is a dummy variable that equals one if the firm ever spawns at least one venture capital-backed entrepreneur. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous 3 years winsorized at the 99th percentile; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; a dummy variable indicating whether the firm was backed by venture capitalists; dummy variables indicating if the firm was located in Silicon Valley or Massachusetts; measures for the firm's patent quality and originality, the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies for each year that the firm is in our sample, though the coefficients are not shown; some include industry-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations within the same 2-digit SIC code.

	Dependent Variable: Dummy Variable Indicating Any Spawning			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Log of chemical patents	−0.0035	−0.0062	0.0059	0.0009
	[−0.35]	[−0.99]	[0.44]	[0.08]
Log of computer and communications patents	0.0921	0.0902	0.0746	0.0729
	[7.14]	[7.26]	[5.71]	[6.11]
Log of drugs and medical patents	0.0755	0.0842	0.0669	0.0811
	[7.66]	[11.71]	[5.32]	[6.97]
Log of electrical and electronic patents	−0.0015	0.0107	0.0105	0.0211
	[−0.09]	[0.79]	[0.73]	[1.56]
Log of mechanical patents	−0.0276	−0.0367	−0.0496	−0.0592
	[−1.95]	[−3.31]	[−3.03]	[−4.11]
Log of other patents	−0.0446	−0.0478	−0.0438	−0.0449
	[−2.85]	[−4.50]	[−2.75]	[−3.11]
Log of real assets	0.0654	0.0544	0.0830	0.0707
	[8.40]	[7.32]	[8.72]	[7.82]
Mean winsorized EBITDA/assets[a]	−0.1451	−0.1290	−0.2911	−0.2570
	[−2.56]	[−2.25]	[−2.99]	[−2.78]
Mean winsorized sales growth over previous year[a]	0.0263	0.0094	0.0259	0.0098
	[1.59]	[0.58]	[1.61]	[0.61]
Mean winsorized Tobin's Q[a]	0.0024	0.0010	−0.0002	−0.0002
	[0.49]	[0.34]	[−0.03]	[−0.03]
Venture capital-backed	0.2024	0.1865	0.1780	0.1688
	[8.56]	[9.54]	[4.89]	[4.71]
Silicon Valley-based	0.1644	0.1947	0.1431	0.1766
	[4.39]	[4.93]	[3.34]	[4.10]
Massachusetts-based	0.1363	0.1405	0.1146	0.1247
	[3.43]	[3.56]	[2.53]	[2.79]

(*continued*)

Table VI—*Continued*

Independent Variables	Dependent Variable: Dummy Variable Indicating Any Spawning			
	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Focused firm	0.0838	0.0592	0.0756	0.0571
	[2.22]	[2.13]	[1.92]	[1.58]
Log of firm age	−0.0271	−0.0389	−0.0205	−0.0327
	[−1.23]	[−1.97]	[−1.19]	[−2.05]
Patent quality	0.0032	0.0039	0.0021	0.0029
	[3.30]	[3.11]	[1.10]	[1.57]
Patent originality	−0.0816	0.0047	−0.1202	−0.0255
	[−1.19]	[0.11]	[−1.75]	[−0.40]
Constant	−0.2417	−0.2460	−0.3253	−0.3321
	[−3.34]	[−4.95]	[−4.69]	[−5.00]
Number of observations	1,370	1,370	1,370	1,370
Adjusted R^2	0.275	0.300	0.277	0.292
Industry-fixed effects	No	No	Yes	Yes

[a]Observations with greater than the 99^{th} percentile are coded as equal to the 99^{th} percentile.

change little across specifications, though patent quality is no longer statistically significant.[14]

C. *The Intensity of Spawning*

In this section, we examine the intensity of spawning, conditional on the firm spawning at least one venture capital-financed firm. Table VII re-estimates the specifications in Table IV for the 515 companies that spawn at least one start-up. The main difference between the coefficients estimated in Table IV and those estimated in Table VII is that although the estimated coefficient of the venture capital dummy is positive, its magnitude is small and statistically insignificant. Thus, one might conclude that prior venture capital backing affects whether a company spawns, but not how much it spawns conditional on spawning.

The estimated effects of location continue to be large, though the coefficient estimate of the Massachusetts dummy is now estimated imprecisely, perhaps because the sample size is so much smaller now. The coefficient of focus is also positive and borderline statistically significant at the 5% confidence level. The estimated effect of quality is also positive and statistically significant. None of

[14] Patent quality in categories 2 and 3 appears to be higher if the company patents little outside those categories. Thus, the negative coefficients of patenting outside categories 2 and 3 may proxy in part for poor patent quality in categories 2 and 3. Excluding the patent quantities in categories other than 2 and 3 increases the coefficient of patent quality, which becomes highly statistically significant.

Table VII

Regression Analyses of Cumulative Spawning Levels Conditional on Any Spawning

The table presents regressions of the cumulative spawning rates for firms, conditional on the firms doing any spawning during our sample period. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the regressions is the natural logarithm of the cumulative number of venture capital-backed entrepreneurs spawned over the entire sample period from these public companies. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous 3 years winsorized at the 99th percentile; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; a dummy variable indicating whether the firm was backed by venture capitalists; dummy variables indicating if the firm was located in Silicon Valley or Massachusetts; measures for the firm's patent quality and originality; the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies for each year that the firm is in our sample, though the coefficients are not shown; some include industry-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations within the same 2-digit SIC code.

	Dependent Variable: Conditional Spawning Level			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Log of chemical patents	−0.0135	−0.0014	−0.0016	0.0182
	[−0.77]	[−0.06]	[−0.05]	[0.52]
Log of computer and communications patents	0.1963	0.2056	0.1333	0.1447
	[4.60]	[4.62]	[4.24]	[3.89]
Log of drugs and medical patents	0.1047	0.1111	0.1064	0.1015
	[9.14]	[8.10]	[3.55]	[2.96]
Log of electrical and electronic patents	−0.0439	−0.0346	−0.0169	−0.0206
	[−1.03]	[−0.80]	[−0.60]	[−0.64]
Log of mechanical patents	−0.0306	−0.0326	−0.0595	−0.0535
	[−0.59]	[−0.77]	[−1.67]	[−1.20]
Log of other patents	−0.0263	−0.0236	0.0120	0.0235
	[−0.51]	[−0.40]	[0.29]	[0.46]
Log of real assets	0.1433	0.0844	0.1870	0.1321
	[7.82]	[3.18]	[6.36]	[4.04]
Mean winsorized EBITDA/assets[a]	−0.1071	0.0090	−0.5791	−0.4348
	[−0.76]	[0.06]	[−2.86]	[−1.86]
Mean winsorized sales growth over previous year[a]	−0.0141	0.0171	−0.0086	0.0279
	[−0.91]	[0.74]	[−0.43]	[1.00]
Mean winsorized Tobin's Q[a]	0.0390	0.0351	0.0418	0.0305
	[5.31]	[4.14]	[2.50]	[1.70]
Venture capital-backed	0.0261	0.0267	0.0229	0.0068
	[0.56]	[0.54]	[0.37]	[0.10]
Silicon Valley-based	0.3091	0.2790	0.2774	0.2528
	[4.81]	[3.81]	[3.94]	[3.52]

(*continued*)

Table VII—*Continued*

	Dependent Variable: Conditional Spawning Level			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Technology Spawning (4)
Massachusetts-based	0.1773	0.1356	0.1565	0.0972
	[1.58]	[1.10]	[1.88]	[1.00]
Focused firm	0.1987	0.1124	0.1469	0.0844
	[1.98]	[1.27]	[1.58]	[0.83]
Log of firm age	−0.0933	−0.0837	−0.0980	−0.1059
	[−1.31]	[−1.74]	[−1.78]	[−1.76]
Patent quality	0.0081	0.0103	0.0070	0.0089
	[2.11]	[1.74]	[1.73]	[2.16]
Patent originality	−0.0352	0.0462	−0.1135	−0.0387
	[−0.30]	[0.46]	[−0.79]	[−0.24]
Constant	−0.2614	−0.1001	−0.5022	−0.3132
	[−1.36]	[−0.51]	[−3.29]	[−1.84]
Number of observations	515	428	515	428
Adjusted R^2	0.440	0.406	0.443	0.401
Industry-fixed effects	No	No	Yes	Yes

[a]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

these effects change substantially when we restrict the dependent variable to the spawning of high-tech firms (column 2) and add industry dummies (columns 3 and 4).

D. The Determinants of Annual Spawning Levels

In this subsection we analyze the determinants of spawning on an annual basis. As discussed above, measuring annual spawning is imprecise given the data we have because in some cases we do not know when the entrepreneur joined the start-up. When we do not have this information, we assume that it occurred at the founding of the start-up. If the start-up is founded before the spawning company goes public, then the observation is dropped from the sample. This approach means that we tend to underestimate to a greater extent the number of spawned entities from companies that have gone public more recently. With this caveat in mind, we present the results of pooled cross-section/time series analysis in Table VIII and a firm-fixed effect analysis in Table IX.

We observe the same basic pattern of results in the first column of Table VIII. Prior venture capital backing, a Silicon Valley or Massachusetts headquarters, and focus are all positively related to the annual spawning levels. The effects are somewhat attenuated by including industry dummies and by limiting the spawning to those in technology-intensive industries as shown in columns 2 and 3 of Table VIII.

Table VIII

Cross-Sectional Regression Analyses of Annual Spawning Levels

The regressions are pooled cross-sectional regressions or the between estimators from fixed effects regressions of annual spawning levels for publicly traded firms. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the regressions is the natural logarithm of the number of venture capital-backed entrepreneurs spawned in a given year from these public companies. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous 3 years winsorized at the 99th percentile; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; a dummy variable indicating whether the firm was backed by venture capitalists; dummy variables indicating if the firm was located in Silicon Valley or Massachusetts; measures for the firm's patent quality and originality; the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies, though the coefficients are not shown; some include industry or firm-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations of the same firm over time.

	Dependent Variable: Annual Spawning Level			
Independent Variables	Total Spawning (1)	Total Spawning (2)	Technology Spawning (3)	Between Estimates from Firm-Fixed Effects Regressions of Annual Total Spawning Levels (4)
Log of chemical patents	−0.0045	−0.0029	−0.0005	−0.0022
	[−0.61]	[−0.37]	[−0.08]	[−0.22]
Log of computer and communications patents	0.1047	0.0935	0.0756	0.1429
	[7.34]	[7.03]	[6.90]	[13.79]
Log of drugs and medical patents	0.0366	0.0354	0.0345	0.0331
	[3.45]	[3.15]	[3.39]	[3.68]
Log of electrical and electronic patents	−0.0161	−0.0069	0.0025	−0.0540
	[−1.94]	[−0.86]	[0.36]	[−4.69]
Log of mechanical patents	−0.0119	−0.0191	−0.0158	−0.0054
	[−1.53]	[−2.17]	[−2.06]	[−0.43]
Log of other patents	−0.0232	−0.0198	−0.0226	−0.0248
	[−3.14]	[−2.52]	[−3.24]	[−1.83]
Log of real assets	0.0281	0.0325	0.0244	0.0277
	[7.73]	[6.68]	[6.20]	[8.04]
Mean winsorized sales growth over previous 3 years[a]	−0.0004	−0.0012	−0.0005	0.0039
	[−0.19]	[−0.54]	[−0.24]	[1.27]
Mean winsorized EBITDA/assets[a]	0.0183	−0.0343	−0.0191	−0.0366
	[0.65]	[−1.09]	[−0.73]	[−0.95]
Mean winsorized Tobin's Q[a]	0.0089	0.0071	0.0037	0.0073
	[2.63]	[2.19]	[1.38]	[2.08]
Log of firm age	−0.0112	−0.0074	−0.0053	−0.0090
	[−2.10]	[−1.34]	[−1.05]	[−1.07]

(*continued*)

Table VIII—*Continued*

	Dependent Variable: Annual Spawning Level			
Independent Variables	Total Spawning (1)	Total Spawning (2)	Technology Spawning (3)	Between Estimates from Firm-Fixed Effects Regressions of Annual Total Spawning Levels (4)
Venture capital-backed	0.0370	0.0193	0.0187	0.0134
	[2.41]	[1.27]	[1.35]	[0.95]
Silicon Valley-based	0.1289	0.1274	0.1217	0.1028
	[4.78]	[4.74]	[5.01]	[6.22]
Massachusetts-based	0.0245	0.0182	0.0106	0.0225
	[1.80]	[1.35]	[0.87]	[1.23]
Focused firm	0.0308	0.0315	0.0295	0.0386
	[3.12]	[3.13]	[3.22]	[2.38]
Patent quality	0.0012	0.0007	0.0008	0.0006
	[2.04]	[1.11]	[1.56]	[0.70]
Patent originality	−0.0163	−0.0252	−0.0084	−0.0207
	[−0.87]	[−1.25]	[−0.48]	[−0.67]
Constant	−0.1392	−0.1665	−0.1239	−0.1738
	[−4.87]	[−5.68]	[−5.08]	[−1.45]
Number of observations	10,914	10,875	10,875	10,914
Adjusted R^2	0.227	0.249	0.217	0.342
Industry-fixed effects	No	Yes	Yes	NA

[a]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

The last column of Table VIII reports the result of the between estimator: regressing firm average annual spawning levels on firm averages of the regressors. This approach is similar to the approach taken in Table IV, but relies on the more imprecise measure of annual spawning as opposed to cumulative spawning. Although the results are all consistent with those observed in Table IV, the coefficients are generally more imprecisely estimated in Table VIII.

Table IX reports estimates of a regression equation with firm-fixed effects. We cannot, of course, estimate the effects of the time-invariant factors such as prior venture capital backing and location. Thus, we include only those variables that change over time. The main question that we can address with this approach is whether firms tend to spawn more when their performance and growth are relatively good or when they diminish. There are two alternative views. On the one hand, spawning may be higher during relatively good times as employees are exposed to more entrepreneurial opportunities. On the other hand, when growth slows or performance weakens, one might expect employees to be more aggressive in pursuing outside entrepreneurial opportunities, since the value of remaining at the company falls.

As before, larger firms tend to spawn more, which is not surprising given the fact that they have more employees and more intellectual capital. The elasticity of spawning with respect to firm size, however, is once again far less than one.

Table IX

Firm-Fixed Effects Regression Analyses of Annual Spawning Levels

The table presents the firm-fixed effects regressions for the sample of publicly traded spawning firms. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable in the regressions is the natural logarithm of the number of venture capital-backed entrepreneurs spawned in a given year from these public companies. The information on entrepreneurs comes from a sample of 15,297 founders of 5,112 venture capital-backed start-ups in the VentureOne database of venture capital financing who received venture capital financing between 1986 and 1999. Independent variables include the natural logarithm of inflation-adjusted firm size; the ratio of the firm's winsorized earnings before interest, taxes, depreciation, and amortization to assets; the firm's sales growth over the previous 3 years winsorized at the 99th percentile; the firm's industry sales growth over the previous 3 years winsorized at the 99th percentile and deviations from that industry sales growth over the previous 3 years winsorized at the 99th percentile; dummy variables indicating sales growth; Tobin's Q for the firm winsorized at the 99th percentile; the natural logarithm of patents in six patent categories; the natural logarithm of firm age; and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies, though the coefficients are not shown; some include industry or firm-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations of the same firm over time.

	Dependent Variable: Annual Spawning Level			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Total Spawning (4)
Log of chemical patents	−0.0018	0.0090	−0.0018	−0.0020
	[−0.25]	[1.43]	[−0.25]	[−0.28]
Log of computer and communications patents	0.0506	0.0319	0.0504	0.0501
	[6.94]	[4.96]	[6.94]	[6.85]
Log of drugs and medical patents	0.0092	0.0062	0.0093	0.0092
	[1.35]	[0.95]	[1.36]	[1.35]
Log of electrical and electronic patents	0.0002	0.0055	0.0002	−0.0001
	[0.04]	[0.97]	[0.04]	[−0.02]
Log of mechanical patents	−0.0076	−0.0068	−0.0074	−0.0077
	[−1.20]	[−1.28]	[−1.18]	[−1.21]
Log of other patents	−0.0001	−0.0036	0.0000	−0.0001
	[−0.01]	[−0.65]	[0.00]	[−0.02]
Log of real assets	0.0375	0.0291	0.0373	0.0392
	[6.29]	[5.56]	[6.27]	[6.47]
Winsorized sales growth over previous 3 years[a]	−0.0059	−0.0037		
	[−3.04]	[−2.08]		
Winsorized deviation from industry sales growth over previous 3 years[a]			−0.0060	
			[−3.08]	
Winsorized industry sales growth over previous 3 years[a]			0.0048	
			[0.37]	
Sales growth of firm in the highest quartile of sales growth				−0.0121
				[−2.09]
Sales growth of firm in the lowest quartile of sales growth				0.0101
				[1.49]

(*continued*)

Table IX—*Continued*

	Dependent Variable: Annual Spawning Level			
Independent Variables	Total Spawning (1)	Technology Spawning (2)	Total Spawning (3)	Total Spawning (4)
Mean winsorized EBITDA/assets[a]	−0.0173	−0.0125	−0.0185	−0.0099
	[−0.74]	[−0.57]	[−0.78]	[−0.41]
Mean winsorized Tobin's Q[a]	0.0006	−0.0015	0.0005	0.0007
	[0.22]	[−0.64]	[0.22]	[0.00]
Log of firm age	−0.0246	−0.0004	−0.0245	−0.0247
	[−1.83]	[−0.03]	[−1.82]	[−1.82]
Focused firm	0.0023	0.0091	0.0023	0.0023
	[0.27]	[1.25]	[0.27]	[0.27]
Constant	−0.0768	−0.1478	−0.0789	−0.0912
	[−1.35]	[−2.92]	[−1.39]	[−1.59]
Number of observations	10,929	10,929	10,929	10,929
Adjusted R^2	0.476	0.438	0.476	0.476

[a]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

Table IX shows that spawning is unrelated to Q and to the EBITDA measure, and only modestly related to lagged 3-year sales growth (this coefficient is statistically significant). The model implies that an increase in sales growth from the 25th percentile to the 75th percentile reduces the log quantity of spawning from 0.089 to 0.085, a change of just 4.6%. It is difficult to determine whether these effects are genuinely small or are modest because of the significant measurement error in calculating annual spawning levels and the fact that the firm-fixed effects absorb much of the heterogeneity in the sample. (To the extent that these variables change little for each firm over time, the empirical test does not have much statistical power.) In either case, however, the results appear to be consistent with the view that employees leave firms not at the peak of their growth rates, but instead when growth rates have fallen; that is, employees pursue entrepreneurial opportunities outside their firms when the rents from staying at the firm are diminished.

The regression also includes the logarithm of age and the firm focus measure. Spawning appears to decline as a firm ages; the coefficient is significant at the 10% confidence level. The coefficient on the focus variable is positive, consistent with our earlier cross-sectional findings, but the estimated effect is statistically insignificant. In this analysis with firm-fixed effects, we can only identify the effect of focus through changes in this variable.

The remaining columns of the table examine slightly different specifications. The second column looks at spawning in high-tech industries. We continue to observe a negative relationship between spawning and sales growth. The third column includes two alternative measures of sales growth: mean industry sales growth over the prior three years and firm-specific deviations from mean sales growth. The results indicate that the firm-specific component of sales growth drives the relationship to spawning.

One might be concerned that what is driving the sales growth results is that firms with large reductions in sales or those that go bankrupt are laying off workers, some of whom find new jobs and some of whom start new companies. If this were true, we would expect to see all of the results coming from an increase in spawning when sales drop and not from a decrease in spawning when sales rise. To examine this possibility, we replace the continuous measure of sales growth with dummy variables for two regions of sales growth: sales growth greater than the 75^{th} percentile of sales growth and sales growth less than the 25^{th} percentile of sales growth. The interquartile range is excluded, so the estimated coefficients are measured relative to this region of sales growth. The results indicate that moving out of the highest quartile of sales growth is associated with significantly greater spawning and that moving from moderate sales growth to the lowest quartile of sales growth is also associated with the more spawning. Though the magnitude of these coefficients is roughly the same, only the coefficient on the high sales growth dummy is statistically significant. This result is inconsistent with the hypothesis that spawning is generated by layoffs.

E. Relatedness of Start-up to Parent

This section examines the extent to which venture capital-backed start-ups enter businesses that are related to those of the firms from which they are spawned. We undertake this analysis to help us distinguish between the competing explanations of our findings. One competing explanation is that our key findings are driven by unobserved differences in the technologies of the firms that spawn many new ventures and those that spawn relatively few new ventures. For example, one of our main findings above is that public firms based in Silicon Valley or Massachusetts are more likely to spawn new firms, as are public firms that were themselves once venture capital-backed. This may simply be because firms in these regions and with prior venture capital backing have technologies that are of more interest to venture capitalists. If, however, we find that these high spawners tend to spawn firms with technologies that are *less* related to their own technologies, it would cast some doubt on this explanation.

Another competing explanation of our results is that the large established corporations based outside of Silicon Valley and Massachusetts are less likely to spawn start-ups because they are actually *more* effective at commercializing the new ideas that are generated internally. If this explanation holds, however, one would anticipate that large established firms would be especially unlikely to spawn related ventures, since such new firms would be especially attractive as internal ventures.

To investigate the relatedness of start-ups to their spawning parents, we first need a measure of relatedness. One possibility is to use the industry codes of the start-up and the spawning parent. We reject this approach because the start-up industry codes from VentureOne are not the SIC codes used in the public company COMPUSTAT database. Thus, one would have to map one set of codes onto the other, an imprecise and coarse process. Moreover, the SIC codes are relatively imprecise in many high-technology industries.

Instead, we measure the relatedness of the two firms based on the patents of the parent company and the patents associated with the industry of the start-up. The logic of this choice is that the patent classification scheme allows us to measure quite precisely the areas in which the parent and start-up firm are active, and thus obtain a reasonable proxy for the degree of interconnectedness. Of course, this approach also has some shortcomings, not least of which is that many of the start-ups in our sample are not in industries that have significant numbers of firms with patents.

We define what it means for spawning and spawned firms to be related to each other as follows. We first look at the distribution of patent classes that characterizes the industry of the spawned firm. We then look at the patents awarded to the spawning firm. We compute how many of the spawning firm's awards are in the patent classes in which most of the patents in the spawned firm's industry fall.

More specifically, the procedure we employ is as follows. For this analysis we use the international patent classification (IPC) scheme. Above, it will be recalled, we employed the technology classification scheme developed by Hall et al. (2001), who divided the patent classes in the U.S. patent classification scheme into 36 distinct categories. Each of these 36 classes encompasses several U.S. patent classes. This classification scheme, while useful as a control, is probably too broad for the purpose of measuring relatedness.

To get around this difficulty, we base the analysis of relatedness on the IPC scheme. The IPC system has its origins in the Council of Europe's 1954 European Convention on the International Classification of Patents for Invention. The classification has been managed by an international (rather than a purely European) agency since 1969. Since that year, U.S. patents have been classified by patent examiners according to both the U.S. and IPC schemes (WIPO (1981)).

The IPC system has at least two advantages over the U.S. classification system (upon which the NBER categories are based). First, the IPC scheme is based on the usefulness of the patent for an industry or profession rather than being based on the structure and function of the patent.[15] Thus, the IPC scheme reflects the economic importance of new inventions, as opposed to the technical focus of the U.S. scheme. Second, the first four levels of the IPC classifications are nested. This is in contrast with the U.S. system, where 435/40 is a subset of 435/39, which is in turn a subclass of 435/34, but 435/41 is not a subclass of any of these (USPTO (2003)). The nonnesting of the U.S. scheme would make it inadequate for our relatedness measure.

Because the IPC classification data is not included in the NBER patent citations data file, we obtain this information from Thomson Delphion, a data vendor. For the public companies in our sample, we simply match the patents

[15] Thus, two biotechnology patents that use different technologies to achieve the same end are likely to be classified in proximate classes in the IPC scheme, but not in the U.S. one.

in our data to the Delphion database and extract the primary IPC classification. Getting the IPC classifications on the start-ups in our sample was more complex because they are generally not included in the NBER database.[16] Thus, we identify their patents by searching for them on the USPTO website (www.uspto.gov). We restrict attention to start-ups in 21 industries with significant numbers of patents: For example, we include wireless communications equipment and biotechnology, but do not include business application software and physician-practice management. There are 1,457 entrepreneurs leaving public companies to start firms in these industries, 28.2% of the entrepreneurs (for which we have industry data) who leave public companies.

For each start-up in these industries, we record the patent numbers of the first five patents they received (although they usually have fewer than five patents). Then for each of the VentureOne industries, we identify all 2-digit IPC patent classes that have at least 5% of the patents in that industry. For example, in wireless communication equipment there are four patent classes with at least 5% of the patents in the industry: measuring and testing (13.8%), basic electric elements (16.0%), basic electronic circuitry (7.5%), and electric communication technique (55.3%), collectively accounting for 92.6% of the patents in this industry.[17] We then normalize these patent-class percentages by the cumulative percentage, for example, dividing 13.8% by 92.6% (14.9%) to get the share of the measuring and testing patent class in all patent classes with a greater share than 5%.

To measure the relatedness of the spawning company to the start-up, we calculate the share of the spawner's patents that are in the main patent classes of the start-up's industry. Because some of the patent classes in the start-up industry are more common than others—for example, in wireless communication equipment, electric communication technique patents are more common than basic electronic circuitry—we weight the patent classes in this calculation by their industry share described in the preceding paragraph. For example, suppose the spawning company has 20 patents in all, five in electric communication technique (with a 59.7% share) and two in measuring and testing (with a 14.9% share), and the rest in other patent classes. Then our measure of relatedness would be $(59.7\% \times 5 + 14.9\% \times 2)/20 = 16.4\%$. The mean relatedness measure in our sample is 27.0% and the median is 22.6%.

We use this measure of the relatedness of the start-up to the spawning parent as a dependent variable in the analysis below. As discussed above, it may be that the high spawners tend to spawn more simply because they have technologies that are more appropriate for venture capital. In this case, we would expect to see more related spawning from companies in Silicon Valley and Massachusetts and from those that were also once venture capital-backed. The regressions in Table X examine this possibility and others.

[16] The assignment of COMPUSTAT identifier codes (CUSIPs) in the NBER patent citations data file was done as of 1989. Firms that went public after 1989 do not have an assigned CUSIP in the file.

[17] In the 21 industries, the cumulative percentage of patents with at least a 5% industry share is typically between 80% and 100%.

Table X

Regression Analyses of Likelihood of Related Spawning

The table presents regressions of the degree of relatedness between a spawning and spawned firm. The sample is derived from public companies listed in COMPUSTAT during the period 1986 to 1999 with patents in either computer and communications or drugs and medical based on the NBER patent citations data file classification scheme. The dependent variable is the measure of relatedness described in the text. Independent variables include the natural logarithm of inflation-adjusted firm size, the firm's sales growth over the previous 3 years winsorized at the 99th percentile, Tobin's Q for the firm winsorized at the 99th percentile, a dummy variable indicating whether the firm was backed by venture capitalists, dummy variables indicating if the firm was located in Silicon Valley or Massachusetts, and a dummy variable that equals one if the firm reports only one industry segment in COMPUSTAT. All regressions include year dummies for each year that the firm is in our sample, though the coefficients are not shown; one includes industry-fixed effects. Heteroskedasticity-consistent t-statistics in parentheses adjust for nonindependence of observations of the same firm over time.

	Dependent Variable: Measure of Relatedness	
Independent Variables	Basic Specification (1)	Industry Dummies (2)
Log of real assets	−0.0226	−0.0151
	[−4.88]	[−4.41]
Mean winsorized sales growth over previous year[a]	0.0288	0.0183
	[3.44]	[4.10]
Mean winsorized Tobin's Q[a]	0.0202	0.0188
	[2.88]	[5.10]
Venture capital-backed	−0.0467	−0.0140
	[−2.00]	[−0.93]
Silicon Valley-based	−0.0462	−0.0339
	[−2.22]	[−2.18]
Massachusetts-based	−0.0803	−0.0567
	[−2.80]	[−2.42]
Focused firm	0.0003	0.0380
	[0.01]	[2.05]
Constant	0.3680	0.2993
	[5.83]	[6.59]
Number of observations	844	844
Adjusted R^2	0.228	0.541
Industry-fixed effects	No	Yes

[a]Observations with greater than the 99th percentile are coded as equal to the 99th percentile.

The independent variables are similar to those in the earlier regressions. (We omit for obvious reasons the patent-based measures.) We present two sets of regressions, both with and without industry-fixed effects. The industry dummies control for cross-industry differences in our relatedness measure.[18]

[18] Some industries have more patent classes represented than others. As a result, in these industries the relatedness measure tends to be lower than in industries with fewer patent classes represented. Industry dummies for the spawned start-up control for the cross-correlation that might follow if the industries with relatively more patent classes also tend to be the ones that are, say, located in Silicon Valley.

The results indicate that companies located in Silicon Valley and Massachusetts tend to spawn *less* related ventures than companies outside these areas. This pattern is inconsistent with the view that the spawning patterns follow mechanically from the greater propensity of firms based in entrepreneurial regions to spawn more because they have technologies that are more relevant for venture capital investment. We similarly find a negative relationship between relatedness and prior venture capital backing of the spawning company; the coefficient is statistically significant in the first regression but insignificant in the other. This is also inconsistent with the view that the higher spawning level of venture capital-backed firms is driven by differences in technology. The view is also inconsistent with the view that established corporations spawn less because they successfully retain related new business ideas in-house. Instead, they seem more likely to spawn related ventures.

The other findings are probably more mechanical in nature. Not surprisingly, larger firms and less focused firms tend to do more unrelated spawning (although the latter result appears only in the second regression). High Q firms and those with high lagged sales growth are also more likely to spawn related ventures. This is probably because the supply of good ideas in the core business is greater than in firms with low Q and low sales growth.

What do these results tell us about the spawning process? At this point, it is difficult to draw definitive conclusions, but we can offer two hypotheses that are consistent with the data. One hypothesis is that firms located in Silicon Valley and Massachusetts are more committed to remaining focused on their core lines of business and exploiting opportunities in their core. This pattern may stem from the fact that remaining focused is a key business value that venture capitalists try to instill in entrepreneurs and one that may have been critical to their success.[19] Thus, these high-spawning entrepreneurial firms in the main regions of venture capital activity may be more prone than other firms to reject new business opportunities outside their core lines. A second hypothesis is that these firms are better than others at identifying business opportunities in their core areas of specialization. In this case, venture capitalists would be less willing to fund new ventures from these companies because of adverse selection concerns. Thus, the new ventures that emerge from these firms are more likely to be outside the core business. At this point, these hypotheses remain purely speculative. We can, however, conclude that the data are inconsistent with the view that the results are driven by systematic differences in the technologies of the high and low spawners or the ability of established firms to retain critical technologies.

III. Conclusions and Suggestions for Future Research

This paper examines the determinants of entrepreneurial spawning, that is, the propensity of publicly traded corporations to spawn new venture capital-backed firms. While entrepreneurial activity has received a tremendous amount

[19] For evidence that supports this claim, see the discussions in Gupta (2000).

of attention from academic researchers and the popular press, the source of new entrepreneurial firms has received relatively little systematic attention. We show that existing public companies are an important source of entrepreneurs for venture capital-backed start-ups, particularly public corporations with patents in areas of interest to venture capital. Younger firms that were backed by venture capitalists themselves and that are located in the main hubs of venture capital activity (Silicon Valley and Massachusetts) are more likely to spawn new firms. Moreover, firms focused on one main line of business are more likely to be the source of entrepreneurial ventures. Firms outside of Silicon Valley and Massachusetts not originally backed by venture capitalists are more likely to spawn businesses related to their core areas of specialization.

Entrepreneurs clearly come from both large bureaucratic firms and young venture capital-backed firms in Silicon Valley or along Route 128, indicating that both Xerox- and Fairchild-type spawning occurs in practice. Our results, however, point to the Fairchild view as a more important determinant of a firm's propensity to spawn a new venture capital start-up. Our analyses suggest that the breeding grounds for entrepreneurial firms are more likely to be other entrepreneurial firms. In these environments, employees learn from their co-workers about what it takes to start a new firm and are exposed to a network of suppliers and customers who are used to dealing with start-up companies. These spawning entrepreneurial firms may also implicitly select for less risk-averse individuals who are willing to bear the greater risks of starting a new firm. We do not encounter much compelling evidence that Xerox-type firms—large, diversified corporations headquartered outside the main regions of venture capital activity and with no prior link to venture capital—are more likely to spawn outside their core line of business.

Our findings have several implications. In particular, they suggest that entrepreneurial activity in a given region has increasing returns (Saxenian (1994)). Stimulating entrepreneurship in a region with few existing entrepreneurial firms is difficult; there may be many individuals with the technological know-how to start a new venture capital-backed firm, but many fewer who know how to start new companies. In addition, the network of suppliers and customers may not be strong enough to support a new venture.[20] Policies that have sought to foster entrepreneurial and venture capital activity by providing capital or investment incentives may not be enough. Instead, regions may need to attract firms with existing pools of workers who have the training and conditioning to become entrepreneurs.

At the same time, the results suggest that the ultimate success (in terms of scale) of individual venture capital-backed firms may be limited. The analysis shows that when growth slows, employees are likely to leave their firms to start new ones. Thus, there may be limits to how big a venture capital-backed firm can get while retaining its most entrepreneurial employees.

[20] Lerner (1999) discusses the powerful political pressures that can lead to the scattering of venture capital funding across regions, as well as presents evidence consistent with this view from one government program to finance small high-technology businesses.

There are a number of related research questions we plan to pursue. We list three of them here. First, we hope to supplement this analysis with a survey of spawned entrepreneurs. What reasons do they give for leaving their firms and starting new ones? How do the responses vary depending on the type of company from which the entrepreneur was spawned? Second, how does spawning affect the parent? In particular, does it have a negative effect on growth and performance of the spawning firm as its most creative employees leave to start new ventures? Finally, how do the characteristics of the spawning firms affect the success of the new ventures? For example, are entrepreneurs from more successful spawning firms more or less likely to be successful themselves? And, how do the characteristics of the spawning firm's patents affect the likelihood of the new venture succeeding?

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