Spawned with a Silver Spoon?[1]

Entrepreneurial Performance and Innovation in the Medical Device Industry

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Abstract

Entrepreneurs in high technology industries often have prior experience at incumbent firms, but we know little about how knowledge obtained at the prior employer impacts entrepreneurial performance. Drawing on previous work from management, economics, and organizational sociology, I assess the impact of prior industry experience on entrepreneurial performance and innovation in medical device start-ups. I find that spawns (ventures started by former employees of incumbent firms) perform better than other new entrants. Interestingly, my findings suggest that this superior performance is not driven by technological spillovers from parent to spawn. Instead, I find that most spawned entrepreneurs do not inherit technical knowledge from the parent firm, contradicting much of the previous literature. To account for the superior performance of spawned ventures, I discuss the different types of non-technical knowledge that are inherited by spawns and explain how these types of knowledge impact new venture performance. These results build on the emerging literature on entrepreneurial spawning and contribute to our understanding of knowledge inheritance between firms. I utilize data from VentureSource, Venture Economics, the NBER patent database, and semi-structured interviews.

1. Introduction

Entrepreneurship in high technology industries often occurs through "spawning" (Gompers et al. 2005, Klepper, 2001, Brittain and Freeman, 1986). This is the process by which former employees of incumbent firms found entrepreneurial ventures in the same industry.[2] Employment at an incumbent firm (the parent) frequently provides a springboard for the incipient entrepreneur to launch a new venture (the spawn). Prospective entrepreneurs can use their experience at an incumbent firm to acquire financial resources, accumulate social capital, augment their technical skills, and identify entrepreneurial opportunities. Once these nascent entrepreneurs found a new venture, their progress may be heavily influenced by the characteristics of their former employer, as they raise capital, establish organizational routines, develop and manage intellectual property, and choose the appropriate business strategy.[3]

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[2] Agarwal et al; 2005 refer to these firms as spin-outs. I use the terms interchangeably in this paper.

[3] Of course, individual characteristics matter greatly as well, and there is a significant literature exploring which individual characteristics relate positively to entrepreneurship

Despite the considerable influence of prior employment on entrepreneurship, few studies have explicitly related attributes of the parent firm to the strategy and performance of the spawned entrepreneurial venture. How then does prior employment impact the entrepreneurial process? Specifically, how does knowledge gained at the parent firm impact the performance and innovative activities of the spawned venture? In this paper, I will investigate whether entrepreneurial spawns perform better than their competitors and assess to what extent spawns incorporate knowledge from the parent firm. A key issue in this literature concerns the type of knowledge that the spawn gains from the parent, and I present some preliminary results on this point as well. In the next section, I will discuss the relevant literature from management, economics, and organizational sociology. I use this prior work to develop 4 testable hypotheses, which I propose in Section 3. Section 4 provides a brief overview of the medical device industry and explains why it is well suited for this study. Section 5 describes the dataset and how it was constructed. Section 6 presents the major results on performance and knowledge inheritance. I offer my conclusions and outline the major caveats to this analysis in Section 7.

2. Literature Review and Theoretical Background

I draw on recent work from management, economics, and organizational sociology on entrepreneurship, and in particular entrepreneurial spawning and spin-offs to develop 4 testable hypotheses. The key findings of prior work suggest that 1) Organizations differ in their propensity to spawn entrepreneurial ventures; 2) Spawns incorporate technical and other types of knowledge from the parent firm, but also differentiate themselves in their business strategies; and 3) The knowledge inherited from the parent firm, along with other characteristics of the parent firm, will impact the performance of spawns.

2.1. Prior Employment and Entrepreneurial Opportunities

While the romantic (and popular) notions of entrepreneurship conjure up images of a college drop-out working out of his parents' garage on the next big thing, most entrepreneurs have significant prior employment experience (Cooper, 1985; Robinson and Sexton, 1994), and many prospective entrepreneurs first identify entrepreneurial opportunities at their previous job (Cooper et al. 1990). In fact, Bhide (1994) found that 71 percent of the founders he studied exploited ideas they came across at their previous employer. Once an employee invents a new technology or identifies a new entrepreneurial opportunity, he may choose to disclose it to his employer or not. Anton and Yao (1995) model this decision, and also theorize about when the innovation is developed at the parent firm or when a spin-off results. In their view, spin-offs occur because of contracting problems between firm and employee, and these new ventures will target niche markets with significant innovations. Thus, how the parent firm designs its internal incentive structure, as modeled by Hellmann (2002), will influence the employee's decision to become an entrepreneur.

2.2. Entrepreneurial Spawning

There is also an emerging literature on why some firms spawn more new ventures than others. Gompers et al. (2005) tests two theories of entrepreneurial spawning. In the first case, employees learn valuable skills and gain access to important social and financial networks through the parent firm's suppliers and customers. Furthermore, employees may even have the opportunity to engage in the entrepreneurial process within the firm through corporate venture

capital units and other internal initiatives. In theory, this type of organizational environment should attract and produce more entrepreneurially minded employees.

In the second case, entrepreneurship is instead a response to a rigid firm bureaucracy that discourages the pursuit of opportunities outside of the core business and penalizes entrepreneurially minded employees for deviating from an assigned task. For many reasons, industry incumbents may be unable to capitalize on disruptive innovations (Christensen, 1997) and internal capital budgeting may favor ongoing projects instead of innovative ideas. Thus, entrepreneurial employees, frustrated with their employer's reluctance to prioritize innovation and exploit new opportunities, will leave the firm to start their own venture.

Gompers and his coauthors find indirect support for the first case in which employees learn valuable skills and gain access to useful social and financial networks at the parent firm. The authors also suggest that parent firms that were once VC backed themselves may establish organizational routines and practices that encourage innovation and entrepreneurial thinking. Still, they do not test explicitly for knowledge flows (technical or otherwise) from parent to spawn.

Klepper and Sleeper (2002) delve into this relationship further, and argue that spin-offs inherit knowledge from their parent firm that shapes their organization, strategy, and performance. In their model, the employee at the parent firm gets access to key information about new innovations and technical developments as well as market opportunities. The employee may then decide to exploit this opportunity himself. Using evidence from the laser industry, the authors find that spin-offs exploit knowledge from their parents but also tend to differentiate themselves from the parent firm. However, it is important to note that the authors use product characteristics, not measures of knowledge flows, to reach this result.

One unresolved question from Gompers et al. (2005) is posed at the end of their paper. The authors ask,

> *"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?"*
>
> Similarly, Burton et al. (2002) also ponder whether "*ventures spawned from prominent employers may be more likely to go public successfully, or {whether} they may be more likely to be acquired…*".

Whether spawns perform better than other entrants is clearly an open question, but it is also important to understand where these supposed performance advantages come from. In particular, to what extent do spawns actually incorporate knowledge or other capabilities from the parent firm that impact performance? For example, spawns may perform better because their prior experience at a prestigious firm is a credible signal of their quality to potential investors, partners, and suppliers. Alternatively, performance advantages may derive from specific knowledge inherited from the parent firm. The question then is, if we demonstrate that spawns perform better, can we also ascertain the difference between the "signaling" component of prior experience that attracts outside financiers, partners, etc. versus the "employee learning" component (discussed both by Klepper and Sleeper (2002) and Gompers et al. (2005)) where spawns use knowledge cultivated at the parent firm to exploit entrepreneurial opportunities?

Furthermore, it need not be technological knowledge alone that is passed from parent to spawn. Agarwal et al. (2004) assert that both technological and marketing know-how can be passed from parent to spawn (they use the term spin-out), using evidence from the disk drive sector. In fact, Agarwal and her co-authors argue that when one type of know-how is not matched by its complement (e.g. a firm with technical know-how but insufficient marketing know-how), employees are more likely to leave the firm to start their own ventures. Thus, the level of technological or marketing know-how in the parent firm is positively related to the spawning rate. Moreover, spawns inherit technical and marketing know-how from their parents, and these capabilities will enhance spawn survival.

2.3. Uncertainty and Inter-Organizational Affiliations

While Agarwal et al. (2004) posit that the technological and marketing know-how of the parent firm will impact the performance of the spawned venture, there is other work suggesting that other parent attributes may be relevant to understanding spawning. Burton et al. (2002) focus on the relative "entrepreneurial prominence" of the parent firm and hypothesize that if a particular parent firm is (a) prominent in the industry and is (b) known for spawning entrepreneurial ventures, then their spawns will be more likely to pursue an innovative strategy and obtain external financing. The authors argue that the prominence of the parent company can reduce the uncertainty for investors deciding whether to finance a new venture.

The work on entrepreneurial prominence is related to the concept of inter-organizational affiliation proposed in Stuart et al. (1999). Since there is considerable uncertainty surrounding new high technology firms, potential exchange partners may rely on affiliates to signal the quality of a new venture (Stuart et al. 1999). In this manner, new organizations establish credibility through their associations with existing organizations (Higgins and Gulati, 2003). Often lacking a finished product, customers, or positive revenue, young companies communicate their credibility to outsiders in a variety of specific ways (Stuart et al. 1999). As Higgins and Gulati (2003) describe in the biotech industry, young firms will establish their legitimacy through associations with prestigious scientists, hiring away top managers from incumbent firms, or by partnering with pharmaceutical companies downstream. As discussed in Stuart et al. (1999), these inter-organizational endorsements will reduce the uncertainty surrounding young firms and allows third parties to make more informed judgments about new ventures.

To summarize then, the prior work on entrepreneurial spawning and spin-offs has emphasized the relationship between the parent firm and the spawn, and in particular has suggested that the parent's technical knowledge, marketing know-how, social networks, and prominence in the industry will impact the performance of the spawn. There has been indirect empirical evidence that spawns inherit various types of knowledge from the parent firm, which subsequently impact its performance. Still, large gaps remain in our understanding of the nature of knowledge inherited by spawns and demonstrating that these knowledge spillovers are actually taking place.

3. Hypotheses

The previous literature offers some theoretical insights into why spawns might perform better than other entrants. In short, the argument rests on valuable knowledge (usually technical) being inherited by the spawn from the parent, but this has been rarely tested. Moreover, with the exception of Agarwal et al. (2004), the distinction between technical knowledge and other types of knowledge is rarely addressed. In this paper, I seek to test whether spawns actually inherit

knowledge from the parent, and if so, how this knowledge impacts performance. I use the prior literature to develop 4 hypotheses on spawn performance and knowledge inheritance. First, as discussed in detail above, prior work in management, economics, and organizational sociology suggests that spawns of large, prominent, firms in the industry will perform better than their competitors. These performance advantages are derived from the lower costs of access to valuable knowledge, skills and experience gained through employment at the parent firm, privileged access to valuable social networks, and the benefits of prominent inter-organizational affiliation for former employees of incumbent firms. These advantages can manifest themselves in several different ways. Timely access to capital is a critical factor to success in entrepreneurship, as several nascent and incumbent ventures are often competing to develop a product at the same time.[4] Hsu (2004) finds the serial entrepreneurs obtain outside funding faster than first time entrepreneurs because their prior experience reduces the uncertainty venture capitalists face in making the funding decision. Prior experience at an industry incumbent will impact time to funding in a similar way, as venture capitalists will face less uncertainty in deciding to fund a spawn rather than a physician with no business experience. In the case of a spawned employee, the affiliation with the parent firm, industry expertise, and valuable social networks may all make it easier to obtain funding more quickly. As implied by Stuart et al. (1999) and Burton et al. (2002), spawns from large incumbent firms in the industry should have an easier time obtaining funding than their competitors.

Thus, I propose hypotheses 1:

Hypothesis 1
Entrepreneurial ventures that have been spawned by incumbent firms in the industry will secure funding more quickly than other entrants, controlling for all observable characteristics

Next, conditional on getting funded, the implications of Klepper and Sleeper (2002) and Gompers et al. (2005) is that spawns benefit from the knowledge and skills gained at the parent firm and should experience better performance in the long run. Agarwal et al. (2004) finds that spawns in the disk drive industry last longer than other entrants and Phillips (2002) also finds that spawned ventures survive longer than other entrants in his study of law firms. Agarwal et al. (2004) argue that spawns will possess superior industry specific knowledge compared to their competitors, which manifests itself into better performance. However, it should be noted that it is quite difficult to measure performance in private entrepreneurial firms. Thus, I propose hypotheses 2A and 2B, using pre-money (private) valuations at the last round of venture capital financing and the successful commercialization of a product as proxies for performance.

Hypothesis 2A
Entrepreneurial ventures that have been spawned by incumbent firms in the industry will have higher valuations at the last round of outside (non-public) financing than other entrants, controlling for all observable characteristics

Hypothesis 2B
Entrepreneurial ventures that have been spawned by incumbent firms in the industry will be more likely to commercialize a product than other entrants, controlling for all observable characteristics

[4] Hsu, 2004

Finally, as suggested by Klepper and Sleeper (2002) and Agarwal et al. (2004), spawns inherit valuable technical knowledge from their parent firm that impacts their own organizational routines, business strategy, and performance. In particular, Agarwal et al. (2004) find that the more technical know-how the spawned venture has, the longer it survives. This work implies that the greater the extent to which spawns incorporate technical knowledge from the parent firm (without directly imitating the parent), the more successful they will be.[5] However, it is difficult to trace the inheritance of this technological know-how across firms. Preliminarily, I examine the relationships between parent and spawn patent portfolios. Therefore, I propose hypothesis 3.

Hypothesis 3
Spawned ventures that incorporate technical knowledge from the parent firm will perform better than other spawns, and other competitors.

It is important to note that I can only test for one type of parental knowledge here—technological know-how—and assess its impact on the performance of the spawned firm. After the empirical results are presented, I will discuss the alternate forms of knowledge inherited by the spawned firm from the parent in Section 6.

4. The Medical Device Industry

The November 1976 meeting of the American Heart Association had a poster session that would revolutionize medicine. [6] Dr. Andreas Gruentzig, dressed in sandals and a leather jacket, presented his research to an audience of skeptical colleagues in Miami, Florida.[7] A young Stanford University trained doctor named John Simpson was enamored with Gruentzig's offbeat idea to use a balloon catheter to clear blocked coronary arteries delivering oxygenated blood to the heart, a procedure called angioplasty.

After tinkering with Gruentzig's design at home, Simpson would eventually found Advanced Cardiovascular Systems (ACS) in 1978, a successful medical device company that helped to create an entirely new specialty within medicine and spawned numerous other medical device firms through its former employees. The entrepreneurial culture at ACS produced the next generation of medical device start-ups that would later commercialize several important medical technologies. [8]

Today, medical technologies are being touted as a potential way to reduce health care costs and improve the quality of care. With industry giants like Medtronic and Johnson & Johnson largely focusing on incremental innovations to their existing products, disruptive innovation has been left largely to physician-entrepreneurs like John Simpson, former employees of industry incumbents like the ACS alums, serial entrepreneurs who found multiple companies, and individuals from outside the industry who develop promising ideas.

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[5] Klepper and Sleeper (2002) make an interesting point that this relationship may be non-monotonic
[6] http://www.ptca.org/archive/interviews/myler1.html Last Accessed April 4th, 2005
[7] Cath Lab Digest
http://www.cathlabdigest.com/cld/displayArticle.cfm?articleID=./200106/cld_200106f6&type=A Last accessed September 10th, 2005
[8] One interview subject I spoke with described ACS as the "university of medical devices" for its reputation as a training ground for future medical device entrepreneurs.

The medical device industry has continued to introduce innovative products, especially in the area of interventional cardiology. The development of bare metal stents and drug eluting stents are the most well known. During the first angioplasty procedures, 30 percent of patients eventually developed restenosis, or re-blockage of the arteries.[9] Cardiac stents were then introduced to remedy this problem. A stent is a tiny steel mesh tube that is used to keep arteries open during procedures like angioplasty and atherectomy. During these procedures, a balloon is inflated and the stent will expand to the size of the artery, staying in place permanently after the procedure is over. Stents were first approved for use in 1994 and are now common in cardiac procedures. Bare metal stents eventually reduced restenosis by 20-50%, a significant improvement.[10]

Still, the simple stents resulted in complications, with scar tissue developing around the stents still sometimes causing re-blockage of the arteries. Many companies, in both biotechnology and medical devices, were actively trying to improve stent technology during the late 1990s and early 2000s. Advances in research led to the development of anti-restenosis drugs, which were quickly seized upon by top stent makers, Guidant, Johnson & Johnson, and Boston Scientific, who tried to combine the new drugs with stents. Johnson & Johnson was arguably most successful in this endeavor, gaining FDA approval for its Cypher stent before its two competitors. The stent market was estimated to be worth $2.6 billion dollars in 2003. The new generation of stents cost $3,000 each, and market analysts expect sales of nearly $5 billion dollars in 2005 for use in 1 million patients (patients often require more than 1 stent).[11]

Today, medical device firms develop and commercialize many kinds of innovative products used by physicians during cardiovascular, neurological, and various other types of medical procedures. These products include diagnostic equipment like CAT Scan machines, therapeutic devices such as pacemakers and surgical instruments like endoscopes. Products are usually marketed and sold directly to healthcare professionals and to supply companies. Overall, medical devices are a growing industry with a market size of $75 billion in 2002 and $1.5 billion venture capital invested in 2003.[12] [13]

The medical device industry is ideal for an empirical investigation of entrepreneurial spawning, since there are a number of large players; Johnson & Johnson, Boston Scientific, Guidant (recently acquired by Boston Scientific), Abbott, Medtronic, St. Jude, and others, surrounded by numerous innovative start-ups. In addition, many employees of the aforementioned large firms have spawned new ventures with varying levels of success. In addition, other medical device entrepreneurs have entered the industry directly from clinical practice or academia. This variation in prior employment is central to the empirical study. The industry is also conspicuously clustered in certain areas of the country, including The San

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9 The Cleveland Clinic Website
http://www.clevelandclinic.org/heartcenter/pub/history/future/intervention.asp Last accessed April 12th, 2005
10 The Cleveland Clinic Website
http://www.clevelandclinic.org/heartcenter/pub/history/future/intervention.asp Last accessed April 12th, 2005

11 The Motley Fool Website
http://www.fool.com/news/commentary/2003/commentary030602am.htm Last accessed April 12th, 2005

12 AdvaMed2004 Report
13 PriceWaterhouseCoopers Money Tree (www.pwcmoneytree.com) Last accessed March 1st, 2005

Francisco Bay Area, Minneapolis, Orange County, CA, and Boston, allowing for considerable employee mobility since individuals can easily change jobs without relocating.[14]

Additionally, patenting is crucial in the medical device industry with over 9000 patents issued by 2003. Patenting of medical devices is usually considered a crucial part of firm strategy in this sector.[15] In addition, academic research is a key component of product development. In many cases, advances in the academic literature spur product development and company formation.[16] Moreover, doctors are not only the primary customers for medical devices, they are often innovators as well. These user innovations are an important source of ideas for incumbent firms and new entrants. Finally, there are many active venture capitalists investing in the industry. In the first 2 quarters of 2004, over $700 million dollars of venture capital was invested in the medical device and equipment sector. Taken together with biotechnology, the life sciences space took in 25 percent of all venture capital in the first 2 quarters of 2004. [17] (See figures 1-4 in Appendix B for general trends regarding venture capital investments in medical device)

5. Data and Methods

5.1. Data Sources

To answer the research questions posed above, I utilize four major data sources:

1. VentureSource's Venture One database
2. Thomson Financial Venture Economics's Venture Xpert database
3. NBER Patent Database
4. Semi-Structured Interviews with 10 Medical Device CEOs

VentureOne and Venture Xpert have been used by many scholars to investigate issues surrounding venture capital and private companies (Kaplan et al. 2002). VentureOne was established in 1987 and tracks firms that have received venture capital financing. The firms are identified through trade press, company websites, and personal contacts with investors. VentureOne surveys the firms and the investors, and updates and verifies the data monthly. Some of the variables include the names and previous employers of the company founders, industry sector, business strategy, and some limited financial information about the new venture (Gompers et al. 2005).

Venture Xpert has similar information on venture capital firms and their investments in private companies. While there are some differences between the databases (see Kaplan et al. 2002), I use both databases together to cross check information. The important variable of prior employment of founders is found in the Venture One dataset.

The NBER patent database has data on nearly 3 million U.S. patents granted between 1963 and 1999 (Hall et al. 2001). I can use medical device patents and citations to analyze innovation among entrepreneurial ventures and incumbents in the industry.

Through industry contacts, I conducted semi-structured interviews with CEO/Founders of privately held medical device companies in my data. The purpose of the interviews was to gain

[14] Almeida and Kogut (1999) discuss the implications of regional mobility among engineers in the semiconductor industry

[15] This fact emerged in my interviews with medical device entrepreneurs and from secondary industry sources.

[16] The birth of "Hypothermia companies" between 1996-1998 was partly based on advances in research on cooling the human body.

[17] Venture One

insights on the reasons medical device employees leave large firms to start new ventures and isolate the mechanisms by which past experience impacts the entrepreneurial process and performance.

The interviews were semi-structured, conducted both on the phone and in-person, ranging from about thirty minutes to three hours. If the interviewee agreed, the conversations were also recorded. To develop the interview protocol, I rely heavily on Phillips and Fernandes(2003), where the authors conducted interviews of entrepreneurs in the professional services area.

5.2. Building the Dataset

I use Venture Source and Venture Xpert to obtain data on private, venture capital backed medical device companies. Searching under the category "medical device", my original dataset included approximately 1000 firms. For each firm, I also obtained data on executives and their career histories, financing rounds and valuations, and liquidity events. If the executive career history listed a public firm, I used the Compustat database and the NBER patent database to obtain information about the parent company. Finally, I also used the NBER patent database to identify patents for technology invented by and/or assigned to the founders, the entrepreneurial firms, and the parent firms. The final dataset was thus a sample of approximately 650 medical device entrepreneurs from 191 firms, their career histories, their patents and citations, financing information, liquidity events, and information on their parent company.[18]

5.3 Constructing Measures

5.3.1 Time To Funding Measure

The time to funding variable is calculated by taking the difference (in days) between the first reported round of outside funding in Venture One and the founding date for the company. While seemingly straightforward, there are several possible problems with this measure. First, the founding dates are reported to Venture One by surveys and may not always be accurate. For example, a few companies list their founding date and their first round of funding on the same day, which is feasible, but may not indicate the true age of the firm. Next, neither Venture One nor Venture Xpert has reliable data on individual or "angel" investments that could have been made prior to the first round of venture capital funding. Without this data, we may observe a lengthy "time to funding" in cases where the start-up is actually being financing by angel investors. In practice however, most successful medical device companies receive venture capital funding, and data on non-VC backed medical device companies is not readily available.[19]

5.3.2 Entrepreneurial Performance

Measuring performance in small, privately held, companies is a difficult task. The conventional measures of performance for large companies, like profits, revenues, and sales, do not always apply and financial information about private firms is closely held. However, since each firm in my data received at least one round of venture capital funding, there exists some common metrics of performance across each of the 191 firms.

As some scholars have asserted, entrepreneurship is concerned with "value creation"[20], and the valuation of the private firm, as assessed by outside investors, is an appropriate measure

[18] This sample may be biased towards more successful firms, where the career histories of founders were easier to obtain.

[19] Even serial entrepreneurs, who might be the most likely to "bootstrap" their own ventures or secure angel funding, often receive traditional venture capital funding in the medical device industry.

[20] Sarasvathy and Wicks (2005)

of the value the venture has created, and thus a comparable performance metric. I thus use "pre-money" valuation, or the valuation of the company (as determined by investors at rounds of non-public financing) as one measure of performance in this study.

Since the pre-money valuation is determined by outside investors through a rigorous analysis of the company's management team, market opportunities, milestones, and intellectual property, it is an appropriate measure for comparison across private firms. In practice, valuations can be determined in a few different ways, either by identifying comparable companies in the industry, using a discounted cash flow model where future earnings are estimated and discounted to present value, or using the replacement value of assets.[21] Hsu (2004) provides some evidence that entrepreneurs may settle for lower valuations to work with prestigious venture capitalists. I will address this point and its potential impact on my results in Section 7.

Since there is considerable variation in the number of rounds of venture capital each firm in my sample has, I only look at the last round of financing and control for the round number and other important variables. This method allows me to compare ventures at the same round of funding, controlling for other observable characteristics. In doing so, I can determine whether the characteristics of the founder impact the firm valuation at a particular round.

As an alternative measure of performance, I also analyze data from the Food and Drug Administration (FDA) on medical device approval. FDA approval is an important milestone for medical device firms and is critical to future rounds of financing. I use the successful approval of a product as a measure of performance for an entrepreneurial venture, controlling for relevant observable characteristics. (It may also be useful to calculate a time to approval measure, but this will depend heavily on unobserved and product specific characteristics.)

These 2 measures of performance are hardly ideal, but are suitable in the context of medical device start-ups, where financial data is difficult to obtain and product approval is a common goal for most start-ups with innovative technologies.

5.3.3 The Spawning Variable and Other Types of Founders

In the previous literature, a "spawn" or spin-off is usually defined by the most recent employer of the entrepreneur. In my discussions with medical device entrepreneurs, engineers, and venture capitalists, I found that the career path in medical devices is often characterized by "big company" experience early on (at firms like ACS, Medtronic, Baxter, Johnson & Johnson) followed by multiple start-up experiences. Thus, there were few entrepreneurs in my data whose last job had been at a large medical device firm, while many founders had worked at a large medical device firm earlier in their career.

Therefore, I define a spawn as an individual who at some point in their career worked at a large medical device (or life sciences) firm before becoming an entrepreneur. Life sciences, which includes pharmaceutical and biotechnology firms, is included because of the similar managerial, regulatory, and clinical challenges involved in product development. I have defined a spawned venture broadly here, but I also ran alternative specifications with the strictest possible definition of a spawn (an entrepreneur whose last job was at an incumbent medical device firm) and the performance results did not change significantly.

Since my spawning variable is at the firm level, entrepreneurial founding teams who have at least one individual who worked at any point in their career at a publicly traded medical device or pharmaceutical/biotechnology firm are considered "spawns" for the purpose of this

[21] Levine (2001)

study. A simple dummy variable, 1 if at least one team member has worked at a public firm in the industry, 0 otherwise, is used to denote a spawn.[22]

Several caveats must be made about defining a "spawn" in this manner. First, I do not have detailed information on how long each individual spent at the large medical device company that is labeled their "parent" for the purposes of this study. Next, Venture One does not have data on what date the individual joined the entrepreneurial venture, so I conducted my own research (interviews, Lexis-Nexis, company website searches) to determine whether the individual is actually the entrepreneur, or an employee who joined later on. In almost all cases, I am able to precisely determine who the founder of the company is and where they worked previously, but it is possible that a co-founder has been omitted in some cases.

Through the information in Venture One and my own research, I classify each of the non-spawn founders into 3 groups: 1) serial entrepreneurs, 2) physicians, or 3) industry outsiders. If an entrepreneurial team has one member who has previously founded a venture in medical device (but is not a spawn), then I code the venture as being founded by a serial entrepreneur.[23] Similarly, if the venture is founded by physicians or researchers coming directly from universities and medical schools, I code the venture as physician founded.(This category includes university researchers so this category could alternatively be called "academic/non-profit researcher") Finally, if the founder has previously worked only outside the industry, I code the venture as having an outsider founder. With these 3 additional categories and the previously discussed spawn category, I have classified all of the founders in my sample into 4 broad categories.

Once again, there are several issues to consider with this approach. First, those ventures coded as physician-founded may have unobserved (to the researcher) involvement from a serial entrepreneur or a former employee of a large medical device firm. I have searched company websites and several other sources to mitigate this concern of the "phantom" founder. There may also be a bias against listing failed ventures or brief periods of work experience in self reported surveys. Furthermore, my analysis largely relies on the Venture One and Venture Xpert databases and the underlying survey instrument used to collect the data.

5.3.4 Control Variables

Since valuations will differ depending on which market segment the firm is in (cardiovascular, spine, etc.), I add controls for the 14 different market segments identified by Venture One. In addition, since valuations of private companies are heavily influenced by macroeconomic factors, I also control for the year in which the valuation was determined. I also add dummy variables for each round of financing. In addition, I have some limited data on firm characteristics, so I include dummy variables for whether a firm works with an Original Equipment Manufacturer (OEM), has received corporate venture capital, has an international distribution channel, a co-marketing agreement, or is shipping a product to an existing customer.[24]

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[22] Alternatively, I could use the proportion of founding team members who are spawns of publicly traded firms in the industry as another measure. Since founding team size was difficult to determine reliably, I chose not to use this measure

[23] It is important to note that some spawns actually have prior founding experience. Although I code their ventures as spawns for now, I later exploit this variation between "serial spawns" and traditional spawns to measure the impact of non-technical knowledge on performance.

[24] Two of the 69 spawned ventures received corporate venture capital from their parent firm

6. Results

6.1. Empirical Strategy

I first use the data from Venture One and Venture Xpert to investigate whether spawns perform better than other entrants, controlling for other important firm characteristics. I then analyze the patents of start-ups and their parents to measure the extent to which spawns incorporate the knowledge of their parent and estimate the impact on performance. Finally, I discuss the crucial role of non-technical knowledge in spawning.

6.2. Some Descriptive Statistics

Descriptive statistics are presented in Table 1. The mean pre-money valuation in the first round is $6.4 million and $40.4 million in the last round. The standard deviation of last round valuation is $62 million. The average firm has been in business for nearly 7 years. Thus, the sample is composed of small, young, medical device firms, and the distribution of the dependent variable is highly skewed.[25]

Each entrepreneurial venture has been classified as having a founder who was spawned from a large medical device company (36%), a serial entrepreneur with no experience at an incumbent firm (25%), a physician (29%) with no past entrepreneurial experience, or an industry outsider (9%). These categories are mutually exclusive. I combine outsiders and physicians into one group and they are used as the excluded group in the regressions.[26]

Table 1.A. presents the top spawning firms in the medical device sector. The familiar incumbent firms like Medtronic, Boston Scientific, Johnson & Johnson, and Baxter are present. Guidant has spawned 9 ventures in my sample, going back to its days as Advanced Cardiovascular Systems.

6.3. Regression Results

In most of the regressions below, I use an OLS specification that regresses my dependent variable on founder characteristics, year, industry segments, round type, and other controls.

Time to Funding=F (Spawn, Serial, Year, Industry Segment) (1)

Valuation=F (Spawn, Serial, Year, Industry Segment, Round, Firm Controls) (2)

In testing each hypothesis, I first regress the dependent variable on the categorical variables that captures the type of firm (spawn, serial, outsider, physician). I then add in round dummy variables, year effects, industry effects, and finally several other firm specific controls mentioned above. When the dependent variable is highly skewed, I use a log specification.

In Table 2, I find evidence that spawns and serial entrepreneurs get funded faster than other entrants.[27] The dependent variable in each of the three specifications is the log of time to funding. In all three specifications, we see that spawns and serials obtain venture capital funding more quickly than other firms, although the result is weaker when industry segment controls are introduced. The size of the effect is economically significant, approximately equal to a 1 year

[25] I do not have reliable data on the number of employees each firm has at each round. In some cases, I can observe the number of employees at the last round. In these cases, the mean number of employees is 57. 90% of firms in the sample have less than 50 employees.

[26] This coding scheme allows the results to be interpreted more easily. I also ran the same regressions using only physicians as the excluded group and the results do not change significantly.

[27] For 17 firms, I do not have reliable data on time to funding so they are excluded from this analysis

difference in the time to funding between spawns, serials, and other entrants. This result could reflect the fact that spawns and serials choose certain industry segments that attract heightened venture capital interest, a sign of the market knowledge that such entrepreneurs acquire. As a result, when we control for the industry segment, the variation in time to funding is less pronounced because I am essentially comparing firms in the same sub-market. I will discuss the implications of this result further in Section 6.

In Table 3, my results demonstrate that spawns achieve higher valuations at the last round of financing. The dependent variable is the log of the pre-money valuation at the last observed round of financing. The results suggest a positive and significant effect for spawns over other entrants.[28] The results are consistently significant at the 5% level until firm level control variables are introduced in the last specification. At that point, the results are still significant at the 10% level. With only 191 firms and controlling for founder characteristics, round, industry segment, and financing year, this is not surprising.[29] The effect size is economically significant, representing valuations of over $10 million higher for spawns and serials than other entrants.

These results imply that spawns achieve better performance, but there are several alternative explanations. First, there may be considerable unobserved heterogeneity in the sample. That is, high-ability individuals may select into large industry incumbents and later start successful entrepreneurial ventures because of their inherent skills, rather than anything they learned at the large company. In this case, we would still observe the predicted effect even if the large company experience itself did not shape aspiring entrepreneurs, help them to identify entrepreneurial opportunities, or provide them access to valuable knowledge.

The central question that remains is: What part of spawn performance comes from the individual himself (embodied with skills possessed before the parent firm hired him) and what part comes from knowledge gained at parent firm? (In addition, what types of knowledge gained at the parent firm matter the most?) While it is impossible to completely separate these two components, I now try to estimate what part of spawn performance is driven by technical knowledge gained at the parent firm by using patent data from parent and spawns.

6.4 Patent Analysis

The empirical results suggest that spawns perform better than other entrants. What accounts for the superior performance of spawns? The prior literature has conjectured that knowledge (primarily technical) spillovers from the parent to the spawn account for these advantages, but has never, to my knowledge, provided evidence to support these claims. Furthermore, theoretical models have predicted that spawns will "look" like their parents in terms of the technologies they develop. This proposition has usually been tested using product characteristics, not the underlying technology. Thus, I first investigate whether spawns are entering into technology areas in which its parent firm is active. Next, I measure technical knowledge spillovers from the parent to the spawn.

I am interested in 2 broad questions:

[28] Although the coefficient on serial is no significant, we cannot completely rule out that they perform as well as spawns. Since the coefficient on spawn is significant in each specification, the results suggest that spawns outperform serials.

[29] I also ran the regressions omitting valuations that were outliers (above the 95% level) and the results remained robust

1) Do spawns patent in the same technology classes as their parent firm and how does this strategic decision impact firm performance?

2) Do spawns inherit technical knowledge from their parent and how do these spillovers impact firm performance?

6.4.1 How related are parent and spawn patents?

I select data from the NBER Patent database on all patents assigned to the spawned firms up until 2002. I then construct patent portfolios for each of the parent firms as well. As predicted by several models of spawning, we expect that spawns will patent in the same area (or in a very similar area) to the parent firm.[30]

69 of the 191 firms with financing information available are classified as spawns. Examining these 69 firms, I first calculate which patent class (IPC classification) these firms are most active in. Since many of these firms are quite small and new, they often have several patents in one primary class and a few more patents distributed across the rest of the patent classes. I then identify the three primary patent classes for the parent firms.[31] Overall, the parent firms have 78% of their patents in three classes.

6 out of the 69 spawned ventures (8%) have the statistical majority of their patents in their parent firm's primary patent class. 23 of the 69 spawned firms (33%) have the majority of their patents in one of the top 3 patent classes for their parent. These descriptive statistics imply that not all spawns patent in the same patent classes as the parent firm.[32] In fact, most spawns patent in classes that account for less than 25 percent of their parent's patent portfolio, or do not have an issued patent in the sample period.[33]

6.4.2 Technological Knowledge Inheritance

I also analyze the citations file from the NBER Patent Database to trace technological spillovers from parent to spawn more precisely. For each spawn patent, I can identify which previous patents it has cited, and begin to understand whether the patented technology draws on work done at the parent firm. There are some reasons why patent citations might not be an appropriate measure of technological spillovers. Spillovers between technologies may occur, even when there is no citation, and alternatively citations might be made when no technological spillover has occurred. For my purposes then, I may be underestimating the amount of technological spillovers from parent to spawn by focusing on patent citations, but alternative measures suffer from the same limitations. I am less concerned about "gratuitous" citing, where spawns cite parents even in the absence of true spillovers. Jaffe et al. (1993) provides a longer discussion about the merits of using patent citations as a measure of technical spillovers.

12 of the 69 spawned firms in my data cite the parent firm and the average citation rate (number of cites to parent/number of total cites) for citing firms is 3%. Of course, the overall citation rate to the parent firm is very low for spawns, around 1% of all citations, which suggests that not all spawns draw on technical knowledge from the parent firm. But some spawns do cite their parents and appear to build on their work, with firms like Genyx Medical and Arterial

[30] In the Klepper and Sleeper model framework, we might view the knowledge that former employees retain from their parent firm to be most useful in technologically-related areas.
[31] To do so, I divide the parent firm's patent portfolio by class and identify the 3 classes with the most patents.
[32] This fact does not preclude the spawn from working in the same product area as the parent, but makes it less likely.
[33] 22 spawned ventures do not have issued patents as of 1999

Vascular Engineering(not in the financing sample) devoting more than 10% of their cites to the parent firm.

There are a few reasons why spawns might not cite their parents even if they are working in a similar area. Perhaps non-compete clauses and other covenants to prevent former employees from taking valuable knowledge outside the firm compel spawns to omit citations to their old firm's patent portfolio. Another reason may be that the spawned employees themselves are non-technical and do not carry with them valuable technological expertise per se, but rather managerial skill.

To account for this, I collect educational, occupational, and patent data on each of the spawned employees in my sample to classify them as technical or non-technical founders. If the founders have an M.D., a science graduate degree, or any patents, I characterize them as a technical founder. 46 out of the 69 spawns have technical founders and I include a dummy variable for this the regressions that follow and my results changed very little.

6.4.3 Creating a Benchmark

The results from the patent analysis reveal that spawns devote 1% of their total overall cites to their parent firm. Without a proper benchmark, we cannot know whether this is significant. Furthermore, a benchmark would also help us to understand whether the citation rates to the parent firm are truly due to the relationship between spawn and parent, instead of the technological position of the parent firm in the space. That is, a spawn may cite their parent firm because the parent firm owns the most important patents in the technological area, not because they are building on the parent's technology.[34]

To address some of these concerns, I create a control set of patents for the spawn patents based on application year, IPC 4 digit class, and grant year.[35] For each of the 792 spawn patents I identify a control patent that has the same application year, same IPC classification, and closest grant date. This method was used in Jaffe et al. (1993). The control patent set is 712 patents, since some control patents match to more than one spawn patent. Intuitively, the difference in citation rates between spawns and controls will be the extent to which the parent-spawn relationship matters in terms of technical spillovers. In other words, the control patent citation rate represents the percentage of citations that would go to the parent firm, if no parent-spawn link existed.[36]

Table 8 presents the top ten cited organizations by spawn patents and the control set. The lists are similar, with prominent medical device companies receiving most of the citations from spawn patents and the control patents.[37] This fact suggests that the control patents are an appropriate benchmark.

For each spawn, the average citation rate (total citations to parent/total citations made) is 1.04%. Assigning each spawn patent a corresponding control patent, I create a control patent portfolio for each spawn. The next step is to calculate what percentage of total cites for the

[34] Alternatively, a spawn might also cite its parent often simply because it is most familiar with its parent firm's patent portfolio.

[35] Of course, we could generate control samples based on other criteria, including patents in the same class and year from other firms in my sample.

[36] A concrete example would be to compare two start-up companies that were both producing a new type of stent. If one of the firms was a spawn of Johnson & Johnson and other was not, we could compare the percentage of citations to Johnson & Johnson in their patent portfolios to discern whether the parent-spawn relationship matters.

[37] Though unreported in this version, an analysis of the citations of the non-spawn firms in the original sample of 191 firms reveals that these firms are also citing many of the same medical device firms, including Medtronic, Baxter, and Advanced Cardiovascular Systems.

control patent portfolio are to the parent firm of the matched spawn firm. The average citation rate to the parent for the control patent portfolio is .00906 or 0.906%.

For each spawn, I calculate the difference between their parent citation rate and corresponding control rate. The average difference is 0.00135 or 0.135%. This difference cannot be shown to be different than zero in terms of statistical significance. Thus, we have strong evidence that most spawns do not inherit technical knowledge from their parent firm in the medical device industry. This result is quite surprising, given the prior literature on spawning and the technical nature of the industry.

6.4.4 Self-Citations

Many of the citations spawns do make to the parent firm are self-citations. In these cases, the founder is citing his own previous work at the parent firm. In this section, I investigate the self-citations in my data set and discuss the implications for understanding technological knowledge inheritance in the medical device industry.

I read each citation to a parent firm patent and coded it as a self-citation in either of the following 2 cases.

1) The founder is the inventor on the citing patent (the spawn patent) and listed on the cited patent (the parent patent).
2) The founder is not listed on the citing patent (the spawn patent) but is listed on the cited patent (the parent patent)

The first case is clearly a self-citation. In this case, a former employee of a large medical device firm founds his own venture and cites his prior patents at the parent firm on the new patents he files. The second case is less straightforward. Looking at the data, I find many well-known technical founders who had several patents at incumbent firms sometimes did not appear on all patents filed by their start-up. Still, in some cases, these patents still cite the founder's work at the parent firm. In these instances, it may be that the start-up is building on the founder's knowledge as in case 1.

Thus, I define self-citation broadly, including case 1 and case 2 citations to ensure that I account for all types of technological spillovers that arise from the founder citing his own previous work. Out of the 262 citations made by spawn patents to parent patents, 38 citations are self-citations. 18 citations are "case 1" types where the founder is on both the citing and the cited patent, and 20 citation are "case 2 "types. The differences between case 1 and case 2 self-citations might have important implications for understanding knowledge inheritance from parent to spawn. Case 1 self-citations reflect the most extreme form of individual-embodied knowledge, since the entrepreneur is citing his own work at his prior employer. The technology (insofar as it can be accounted for by patents) of the medical device start-up is primarily based on individual knowledge in this case. In Case 2, employees of the new venture cite the founder's work at the parent firm, implying that the knowledge has now been shared among a larger group of employees. While in both cases, the start-up is building on knowledge from the parent firm, the second case might be considered a better example of a technological spillover since the technical knowledge is being transferred among individuals.

Doing the same calculations as above, the average parent cite rate (now excluding self-cites) is 0.862%, which is not statistically different from the control rate. These results confirm that most spawns are not citing their parent firm, but those that do sometimes use self-citations. In these cases, the individual founder is the conduit for technological spillovers from parent to

spawn. This pattern suggests that a significant portion of technical knowledge inheritance in the medical device industry is being driven by entrepreneurs who cite their own prior work. Do these spawned ventures perform better than other entrants because of the technical knowledge they bring from the parent firm?

6.4.5 The Impact of Relatedness and Inheritance on Performance

After demonstrating that most spawns do not inherit technical knowledge from their parents, we would like to know if the few spawns that do build on their parent firm's technology perform better. To differentiate between spawns who inherit technological knowledge from their parent and those who do not, I run the same performance regressions as above, except with new variables indicating how related the spawn's patents are to the parent. I create 4 dummy variables, Spawn Unrelated (for those spawned firms that did not have the majority of their patents in their parent's top three patent classes), Spawn Related (for those spawned firms that do patent predominantly in one of their parent's top three classes), Spawn Simple (for those spawned firms that do not cite their parent), and Spawn Tech Inheritor (for those spawned firms that do cite their parent).

The spawn variable in the earlier analysis is now replaced by Spawn Related and Spawn Unrelated in one model, and Spawn Tech Inheritor and Spawn Simple in another model.[38] The purpose of these regressions is to estimate what part of superior performance for spawns is derived from spawns that "look like" their parents in terms of innovative activities or those spawns who benefit from technological spillovers from the parent firm.

The results are presented first in Table 4. As before, the dependent variable is the log of the pre-money valuation at the last round of non-public financing. Here, we see some limited evidence that spawns that patent in related areas perform better, but once the industry segments are introduced, we cannot claim that this group of spawns outperforms other spawns.

Table 5 shows the results of the same model, except with Spawn Tech Inheritor and Spawn Simple as the main explanatory variables. Here, we find no definitive evidence that spawns that cite their parent's patent portfolio perform better.[39] Thus, I find no support for the claim that spawns that inherit technical knowledge from the parent firm perform better than other entrants.

Table 6 presents the results from an alternative probit model using product approval as the binary dependent variable for performance.

Pr (Product Approved=1)=F (Spawn Unrelated, Spawn Related, Serial, Year, Industry Segment, Round, Firm Controls) (3)

I find that spawns that are more related to their parents are more likely to get FDA approval. Interestingly, the main effect for spawns is not significant, which means that hypothesis 2b is not confirmed. Rather, only certain spawns (those related to their parent) seem to outperform their competitors in terms of obtaining FDA approval. Table 7 presents results of a

[38] In the first model, the "Spawn" variable in equation (2) is replaced by "Spawn Unrelated" and "Spawn Related". Each of the 69 firms previously coded as spawn are recoded according to relatedness criteria described above. In this case, 23 of the 69 firms are coded as "Spawn Related" and the rest are coded as "Spawn Unrelated". The other categorical variables remain the same. In the second model, the process is the same, except 12 of the 69 spawned firms are coded as "Spawn Tech Inheritor" and the rest as "Spawn Simple".

[39] If anything, the evidence suggests that spawns who do not cite their parent have higher valuations

hazard specification that allows for censoring. We see that spawns who are working in related areas to their parents get products approved by the FDA faster.

These results indicate that spawns who work in technology areas closely related to their parents are more likely to get a product approved by the FDA and also navigate the process more quickly. This result is particularly interesting since I also find that technical spillovers between parent and spawn are not extensive and they do not impact performance. How then, can these results be reconciled?

These spawns who patent in the same area as their parents may also have other complementary knowledge that is useful to obtaining approval for products in therapeutic segments. If a former employee of Medtronic starts a new venture around cardiac rhythm management (CRM) (an important area for Medtronic) for example, he may possess regulatory and marketing knowledge that helps his new venture to get a product approved. While the new venture may not cite Medtronic on its patents or build directly on an existing Medtronic technology, these other types of knowledge gained at the firm could be useful as well. Furthermore, it could be that the employee's prior experience at Medtronic alerted him to entrepreneurial opportunities in CRM in the first place. I explore the importance of non-technical knowledge below.

6.5. Implications

What do the empirical results suggest? After establishing first that spawns perform better than other new ventures, we see some evidence that this superior performance is being driven by firms that patent in related areas to the parent firm. Still, I do not find evidence that spawns who cite their parent firm's patent portfolio perform better. Most importantly, I find that spawns do not cite their parent firm very much (compared to a control group), which belies the conjecture that spawns inherit technical knowledge from the parent firm.

If not technical knowledge inheritance, what else could be driving spawn performance advantages? In my interviews, several explanations were given. First, many spawned employees inherit other types of non-technical knowledge from the parent firm, such as regulatory knowledge (understanding both the FDA approval process and the Medicare reimbursement process), marketing knowledge (especially regarding how to market to physicians), and how to identify new market opportunities in the medical devices. In most cases, these types of knowledge were suggested as being more important than technical knowledge inherited by the spawn from the parent.

For example, the management team of Acorn Cardiovascular, also included in this dataset, believed they were close to FDA approval in 2002 for their device that helps to shrink enlarged hearts, but the FDA instead recommended a much larger clinical trial that ended up taking three more years and costing the company $30 million.[40] Acorn acknowledged that the slow enrollment in their earlier trials (which was part of the reason for the original delay) could have been predicted since Medtronic and Guidant had also had similar problems enrolling patients in their trials for similar devices.[41] Former employees of large medical device firms who have managed clinical trials often have crucial knowledge that can speed up the approval process.

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[40] McCartney (2005)

[41] IN VIVO Business and Medicine Report (Summary) February 2004, Vol. 18, No. 2. Windhover Information Inc. http://www.windhover.com/contents/monthly/exex/e_2004800038.htm; Last accessed September 11th, 2005

Importantly, interviewees stressed the importance of prior experience in identifying entrepreneurial opportunities. Employees at large device firm often participated in strategic analysis of their competitors, and were well aware of which segments were being filled up by new start-ups and where new opportunities existed. Similarly, marketing products to physicians provided valuable insight into what new devices might look like and who might buy them.

I find some evidence that spawns target segments where entrepreneurial opportunities are most likely to exist. When I introduce segment controls into my specifications, the impact of spawn on performance is decreased, suggesting that between segment variation accounts for a significant part of the performance advantages for spawns. This trend implies that spawns target particular segments where market opportunities are large, and as a consequence, venture capitalists are active in.

In addition, the finding that spawns who work in areas related to their parent perform better also suggests that identifying profitable opportunities is an important component of success for these firms. After all, it is most likely that employees will gain knowledge in those technological areas where the firm is active. I find that the most successful spawns enter these related areas, but do not directly build on the technology of the parent firm.

While it might seem surprising that some medical device entrepreneurs leave their parent firm without specific technical ideas, my research indicates that this model is fairly common. For example, Mike Hooven, the founder of Atricure, began his job at Johnson & Johnson with the expressed intention of starting his own medical device firm as quickly as possible.

According to Hooven:

> *"I told my superiors right from the start that I wanted to work here for about five years, get the experience, and make the contacts so I could start my own business and sell products back to the J&J's of the world,"*[42]

Interestingly, when Hooven left in 1994 to start his own company, he did not know exactly what clinical area he would specialize in. Instead he met with doctors to figure out what clinical needs were not being addressed, and eventually founded Atricure to focus on atrial fibrillation, a major cause of stroke and congestive heart failure.[43] His experience at Johnson & Johnson had helped him identify new entrepreneurial opportunities, rather than a specific technical idea.

In sum, my results suggest that spawns do perform better than other entrants, but that technological knowledge inheritance is not the major reason. Instead, non-technical types of knowledge help spawns in the regulatory process, marketing to physicians, and identifying profitable market opportunities to pursue. Even in a highly technical industry such as medical device, it would seem that these types of knowledge are more important.

6.5.1 An Empirical Test for the Non-Technical Component of Knowledge

It is difficult to measure these non-technical forms of knowledge as precisely as I have measured technical knowledge inheritance. Using patent data, I was able to identify which spawns had inherited technical knowledge from the parent firm. I could not measure however,

[42] INVIVO Business and Medicine Report, March 2002, Windhover Information Inc.
[43] INVIVO Business and Medicine Report, March 2002, Windhover Information Inc.

whether these spawns possessed other types of non-technical knowledge. One coarse method to differentiate between spawns would be to examine which spawns also have prior founding experience. As mentioned above, many spawns had several jobs in between their experience at a large firm and the start-up listed in my data, including founding previous ventures.[44] Prior founding experience could allow an entrepreneur to acquire many of the non-technical types of knowledge listed above, especially identifying entrepreneurial opportunities and management skills. Thus, we might think that those spawns with prior founding experience possess important non-technical knowledge that my interviewees have suggested are crucial to success.

I divide spawns into 2 groups based on those that have prior founding experience and those who do not. Using these new categories, "serial spawn" and "spawn", I run the same performance regressions as above. The results are presented in Table 9. We can see some evidence that serial spawns (spawned employees who have already started at least one venture) perform better than other spawns. This result implies that prior experience at industry incumbents coupled with founding experience will result in superior entrepreneurial performance compared to prior experience at industry incumbent alone. These results also support the importance of non-technical knowledge in influencing entrepreneurial performance.

6.5.2 A Variant on Spawning

The results suggest that technical knowledge inheritance is less important in impacting the capabilities of start-ups than previously documented. However, if the technologies for new medical device entrants are not coming from incumbent firms, where are new medical devices conceived? My interviewees described a spawning process that is slightly different from the Gompers et al. (2005) and Klepper and Sleeper (2002) perspectives. Rather than ideas coming from ex-employees of large companies, the innovative ideas often come from the users themselves, in this case physicians conducting research (a fine example of user innovation). When a physician discovers a new way to address a clinical need and/or builds a new device, a venture capitalist is usually a key intermediary is matching a manager from a large firm with the physician/inventor. These contacts are often made at medical conferences or through industry associations. This model of spawning is more nuanced than the previous literature and deserves closer inspection.

The start-up Velocimed, founded in 2001 and included in this study, is a typical example of this variant of spawning. The idea for the firm came from Dr. Dennis Wahr, formerly director of interventional cardiology at St. Joseph Mercy Hospital in Ann Arbor, Michigan, who invented an embolic protection device.[45] The device worked in a novel way to remove embolic debris during interventional procedures by blocking and reversing the flow of the treated vessel. Wahr had previously participated in clinical trials to test other firms' devices, including the popular Guidewire device produced by Medtronic.[46] Ironically, he teamed up with 2 former executives from Boston Scientific, another incumbent medical device firm, to form Velocimed around his embolic protection device. Interestingly, Wahr was also CEO despite being the "scientific" founder.[47] The market for embolic protection is estimated to be in the hundreds of millions of

[44] To be classified as a serial entrepreneur in the previous specifications, the entrepreneur was required to have no prior experience at an incumbent medical device firm. Thus, spawned entrepreneurs with prior founding experience were coded as spawns.
[45] Reilly (2003)
[46] Reilly (2003)
[47] Riverwest Venture Partners, http://www.rivervest.com/newsletter/newsletter3.pdf, Last Accessed September 6th, 2005

dollars, and the combination of an unmet clinical need, huge market potential, and experienced executive team guided Velocimed through 4 rounds of venture capital funding.[48] The company was eventually acquired by St. Jude Medical in 2005 for $74 million. [49]

If this model of spawning is prevalent in other industries as well, we must refine our current models of the process accordingly. After all, the theoretical models as they stand now assume that all valuable knowledge resides in the universe of all existing firms and their employees, while in reality this may not be the case. Employees may leave large firms to be matched with physician-innovators and exploit an entrepreneurial opportunity that was never available to their prior employer at all, which challenges many assumptions of the current literature. For example, some of theoretical literature models an employee deciding whether or not to reveal his invention to the firm. In reality, the employee may be weighing an offer to found a start-up based on technology outside of the firm, which would change the contracting problem considerably. In Anton and Yao (1995) for example, one possible outcome is duopoly profits shared between the employee-inventor and the firm. In the case where the employee is working with someone outside the firm, this outcome might not exist. Future research may seek to incorporate this variant of spawning by incorporating it into theoretical models and empirical testing.

7. Discussion

While we know that many high technology ventures are founded by former employees of incumbent firms in the same industry, we know little about how well these spawns perform and to what extent they incorporate knowledge from the parent firm. In this paper, I analyze performance and technical knowledge inheritance for spawns in the medical device industry. I find that spawns do obtain funding more quickly than their competitors (excluding serial entrepreneurs). I also find that spawns receive higher valuations at round, compared to other entrants. These results imply that spawns perform better than other entrants, a finding that has been documented in the prior literature.

Most interestingly though, I find little evidence that technical knowledge gained at the parent firm is a large component of the superior performance of spawns in the medical device sector. Rather, preliminary results and interviews suggest that non-technical types of knowledge acquired at the parent firm, such as the ability to identify entrepreneurial opportunities, seem to drive spawn performance. This is an important contribution to the existing literature, which has hypothesized that spawns inherit technical knowledge from the parent but has rarely demonstrated it empirically.

I examine spawn and parent patent portfolios in detail to measure technological relatedness between firms. I find that not all spawns patent in the same technological areas as the parent. I also construct a set of control patents and find that spawned firms in the medical device sector do not cite their parents more than expected. After concluding that technical knowledge inheritance is probably not the source of superior spawn performance, I discuss other types of non-technical knowledge that impact performance of spawned ventures. I preliminarily test the importance of non-technical knowledge and find that it may account for some of the advantages spawns have over other entrants.

In addition, I describe a more nuanced view of spawning than the previous literature, whereby university researchers or practicing physicians join together with spawned employees

[48] Reilly (2003)
[49] Velocimed Corporate Website, www.velocimed.com/StJude.pdf Last Accessed September 6th, 2005

from incumbent firms to form new ventures. This variant of spawning deserves more attention, as the technical knowledge possessed by the start-up may not be derived from the parent firm, which might have different implications for performance. In these cases, it may be the managerial, regulatory, and industry specific knowledge that spawned employees bring to the new enterprise that are most important, rather than technical knowledge. Investigating the different types of knowledge gained through prior employment is an area for future research.

Furthermore, I have constructed a unique dataset which has yielded several important descriptive contributions as well. The medical device industry has been understudied in the academic literature, and not studied at all in the context of spawning. As Klepper (2001) points out, the small existing literature on spawning has only focused on a few industries, so this evidence from the medical device sector is important for making improvements to existing theory and guiding the direction of future empirical work.

I find that spawns are common in the medical device industry and that a handful of serial entrepreneurs account for a large part of new entrants. With the exception of Hsu (2005), few scholars have empirically examined serial founders. Through my fieldwork, I came across the names of the same 5-7 serial entrepreneurs who have started multiple successful companies in the medical device industry. These founders were described as having the "Midas touch" for attracting capital to new companies, recognizing entrepreneurial opportunities in unmet clinical needs, and helping to develop nascent technologies. I plan to investigate these founders and their companies in future work.

Despite these results, there are several significant alternative explanations that cannot be definitively dismissed. It is possible that the large medical device firms simply recruit the best and brightest employees, who, regardless of their work experience, would later have become successful entrepreneurs. In this case, the employee learning component of spawning would be a red herring; the screening process of the parent firms would actually be driving success for spawned entrepreneurs. While I cannot rule out this possibility entirely, the interviews point to a stronger impact of employee learning rather than parent screening. My interview subjects frequently discussed the product development process at the parent firm and the valuable lessons they learned from it.

Furthermore, this alternative explanation that "good people work for good firms" does not explain why spawns that "look like" their parents perform better. If spawn performance were driven completely by screening, how can we account for the fact that those spawns who rely most on the parent firm do better than those spawns who work in entirely different areas?

Next, the coding of the founding teams is heavily dependent on the data from Venture One and Venture Xpert and my own research, which may be biased by unobserved trends. To mitigate this, I have cross checked my coding and run alternate specifications to ensure the robustness of the results. In addition, patents are not necessarily the best way to track technology flows in the medical device industry and I could be missing knowledge transfer that is not codified in patents. Judging from the perceived importance of patents in the industry and the interviews, I am less worried about this issue than the other caveats I have described above.

Also, there may be additional unobserved spawning of medical device employees into other industries, like biotechnology, which I would not observe. Thus, this study only applies to medical device employees who start ventures in the same industry, and cannot speak to what valuable knowledge these individuals may carry with them to other fields. It is likely that the knowledge gained at the parent firm is most important for spawns in the same industry, so the

impact of prior experience on spawn performance is likely biased upwards in this study since I do not consider spawns in different industries.

It is also possible, as Hsu (2004) suggests, that entrepreneurs accept lower valuations to work with more prestigious venture capitalists. This fact would actually seem to strengthen my results. If spawns are more likely to be working with prestigious venture capitalists, we would observe lower valuations during rounds of financing. My results imply that spawns receive higher valuations at their last observed round than other entrants, so these estimates might be biased downwards if spawns are not accepting their best offer. In other words, I may be underestimating the performance advantages of spawns since these firms may be worth more than their valuation.

Furthermore, pre-money valuation is not an ideal metric for performance for reasons discussed above. In particular, without detailed knowledge of capital equipment, licensing agreements, and detailed financial information, comparisons between pre-money valuations should be considered carefully. As a robustness check, I use other dependent variables such as product approval to measure performance. Still, measuring performance of private companies, some without products on the market, is a noisy process and always open to criticism.

Finally, I only measure (somewhat indirectly) technical knowledge inherited by the spawn from the parent, and do not empirically account for other types of knowledge, including managerial, regulatory, and marketing knowledge. It is difficult to measure this type of knowledge reliably and my data limitations preclude me from addressing this more comprehensively. Ideally, we would also like to have data on the FDA approval process and Medicare reimbursement experience for all of the medical device entrepreneurs in my sample, but such data might be difficult to obtain. Unless a spawned entrepreneur formally held the title of vice president of regulatory affairs (which almost none of the entrepreneurs in my sample did), it would be difficult to assess and compare the regulatory experience of the individuals in my sample.[50]

There are several interesting research questions to pursue based on the results of this paper and other work on spawning. One of the weaknesses of the literature is the inability to refute the "good people work for good firms" explanation for the seemingly large effects of inter-organizational affiliation and prominence. In particular, it would be useful to understand what variables mediate the impact of inter-organizational affiliation for the spawn. Is the effect stronger in the same industry or for employees who were more senior at the parent firm? That is, does the parent firm's reputation matter more for some spawns than others?

We may also be interested in how spawning impacts the subsequent performance of the parent firm. (Jaffee and McKendrick, 2005) When valuable human capital leaves the firm to start a new venture, what is the impact on the parent firm? Also, in studying technological spillovers, it may be enlightening to investigate whether parent firms eventually cite their spawns as evidence that knowledge can travel from parent to spawn and back again.

Finally, when examining the impact of working at an incumbent firm versus starting an entrepreneurial venture, research should focus on differentiating the types of knowledge that can be acquired in each case, and explore how this knowledge is used by individuals who have done both. The spawned entrepreneurs with entrepreneurial experience are interesting candidates for further research, since they presumably embody much of the valuable technical, industry-

[50] Another alternative would be to develop a coarse measure of FDA approval and CMS reimbursement experience at the parent firm level, but we could not know how much experience any particular spawned entrepreneur had with either process at the parent firm.

specific, regulatory, and managerial knowledge (taken together to embody "the silver spoon") necessary to launch successful entrepreneurial ventures.

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Table 1. Descriptive Statistics

Variable	**N**	**Mean**	**S.D.**	**Min**	**Max**
First Round Pre-Money Valuation (MM)	191	6.4	6.6	0	39.3
Last Round Pre-Money Valuation (MM)	191	40.4	62	0.5	499
Spawn	191	0.36	0.48	0	1
Serial	191	0.25	0.43	0	1
Physician	191	0.29	0.46	0	1
Outsider	191	0.09	0.29	0	1
age(yrs)	191	6.7	2.9	0.67	18.9
financingrounds	191	4.7	2.4	1	13
CorporateVC	191	0.14	0.34	0	1
OEM	191	0.07	0.26	0	1
GenDistr	191	0.13	0.34	0	1
CoBrdMkt	191	0.05	0.22	0	1
GlobalDistr	191	0.09	0.29	0	1
JointRD	191	0.06	0.23	0	1
Customer	191	0.1	0.3	0	1

Table 1.A. Top Spawners in Medical Device

Parent	**# of Spawns**
Medtronic	11
Johnson and Johnson	9
Guidant	9
Baxter	5
Nellcor	4
Pfizer	3
American Hospital Supply	2
BSX	2
Bard	2
CardiacThoracic Systems	2
Intec Systems	2

Table 2: Regression Estimates of Determinants of Time To Funding

Variable	(1)	(2)	(3)
Spawn	-0.967***	-0.689**	-0.563*
	(.255)	(0.267)	(0.312)
Serial	-1.08***	-0.740**	-0.522*
	(0.282)	(0.289)	(0.302)
Constant	6.027	6.306	6.426
	(0.146)	(0.000)	(0.587)
Year Effects	N	Y	Y
Segment Effects	N	N	Y
N	174	174	174
R Squared	0.102	0.228	0.307

Robust standard errors in parentheses

* significant at 10% level ** significant at 5% level; *** significant at 1% level

Table 3. Semi-Log Regression Estimates of the Determinants of Last Round Of Outside Financing

Variable	(1)	(2)	(3)	(4)
Spawn	0.358***	0.372***	0.322**	0.283*
	(0.137)	(0.136)	(0.146)	(0.146)
Serial	0.232*	0.258*	0.210	0.175
	(0.135)	(0.140)	(0.142)	(0.149)
Constant	2.855	1.187	1.111	0.852
	(0.135)	(0.404)	(0.387)	(0.516)
Round Dummies	Y	Y	Y	Y
Year Effects	N	Y	Y	Y
Segment Effects	N	N	Y	Y
Firm Controls	N	N	N	Y
R-squared	0.69	0.7	0.72	0.73
Observations	191	191	191	191

Robust standard errors in parentheses

* significant at 10% level ** significant at 5% level; *** significant at 1% level

Table 4. Semi-Log Regression Estimates of the Determinants of Last Round Of Outside Financing

Variable	(1)	(2)	(3)	(4)
Spawn-Unrelated	0.323**	0.347**	0.307*	0.264
	(0.152)	(0.151)	(0.163)	(0.163)
Spawn-Related	0.436**	0.428**	0.36*	0.327
	(0.175)	(0.180)	(0.197)	(0.202)
Serial	0.231*	0.258*	0.211	0.175
	(0.136)	(0.141)	(0.143)	(0.149)
Constant	4.696	1.187	1.109	0.855
	(0.136)	(0.408)	(0.390)	(0.52)
Round Dummies	Y	Y	Y	Y
Year Effects	N	Y	Y	Y
Segment Effects	N	N	Y	Y
Firm Controls	N	N	N	Y
R-squared	0.69	0.7	0.72	0.73
Observations	191	191	191	191

Robust standard errors in parentheses

* significant at 10% level; ** significant at 5% level *** significant at 1% level

Table 5. Semi-Log Regression Estimates of the Determinants of Last Round Of Outside Financing

Variable	(1)	(2)	(3)	(4)
Spawn Simple	0.359**	0.373***	0.322**	0.285*
	(0.142)	(0.141)	(0.150)	(0.152)
Spawn-Tech Inheritor	0.353	0.364	0.323	0.268
	(0.222)	(0.229)	(0.257)	(0.273)
Serial	0.232*	0.258*	0.21	0.175
	(0.136)	(0.141)	(0.143)	(0.149)
Constant	3.924	1.187	1.111	0.849
	(0.222)	(0.407)	(0.389)	(0.526)
Round Dummies	Y	Y	Y	Y
Year Effects	N	Y	Y	Y
Segment Effects	N	N	Y	Y
Firm Controls	N	N	N	Y
R-squared	0.69	0.7	0.72	0.73
Observations	191	191	191	191

Robust standard errors in parentheses

* significant at 10% level; ** significant at 5% level *** significant at 1% level

Table 6. Probit Regression Estimates of the Determinants of FDA Product Approval

Variable	(1)	(2)	(3)
Spawn-Unrelated	-0.015	-0.093	-0.105
	(0.095)	(0.101)	(0.103)
Spawn-Related	0.422***	0.365***	0.361***
	(0.098)	(0.117)	(0.121)
Serial	0.038	-0.029	-0.041
	(0.094)	(0.106)	(0.109)
FinancingRounds	0.035**	0.029*	0.022
	(0.015)	(0.017)	(0.017)
Segment Effects	N	Y	Y
Firm Controls	N	N	Y
Pseudo R Squared	0.08	0.17	0.20
Observations	191	184	184

Robust standard errors in parentheses (Marginal Effects Reported)
* significant at 10% level; ** significant at 5% level *** significant at 1% level

Table 7. Hazard Model-Time to Product Approval

Variable	(1)	(2)
Spawn Unrelated	-0.069	-0.242
	(0.315)	(0.322)
Spawn Related	0.888***	0.512**
	(0.291)	(0.299)
Serial	0.172	-0.041
	(0.302)	(0.322)
Segment Effects	N	Y
R-squared	0.02	0.69
Observations	191	191

Robust standard errors in parentheses

* significant at 10% level; ** significant at 5% level *** significant at 1% leve

Table 8. Patent Analysis

	Spawn	Control
Total Number of Patents	792	712
Top Ten Cited Orgs	Target Therapeutics, Inc. Cordis Corporation Advanced Cardiovascular Systems, Inc. Devices for Vascular Interventions Olympus Optical Co; Ltd Sci-Med Life Systems, Inc. Medtronic, Inc. Danek Medical, Inc. Cardiovascular Imaging Systems, Inc. Cook Inc.	Advanced Cardiovascular Systems, Inc. Medtronic Inc. United States Surgical Corporation Cordis Corporation Olympus Optical Co; Ltd Everest Medical Corporation 3M Baxter International Inc. ValleyLab, Inc. General Electric Company
Citation Rate to Parent	1.040%	0.906%

Table 9. Semi-Log Regression Estimates of the Determinants of Last Round Of Outside Financing

Variable	(1)	(2)	(3)	(4)
Serial Spawn	0.394**	0.438**	0.392**	0.339*
	(0.166)	(0.170)	(0.189)	(0.188)
Spawn	0.332**	0.324**	0.276	0.248
	(0.159)	(0.156)	(0.169)	(0.174)
Serial	0.232*	0.259*	0.215	0.18
	(0.136)	(0.140)	(0.143)	(0.150)
Constant	2.855	1.162	1.083	0.835
	(0.136)	(0.413)	(0.401)	(0.529)
Round Dummies	Y	Y	Y	Y
Year Effects	N	Y	Y	Y
Segment Effects	N	N	Y	Y
Firm Controls	N	N	N	Y
R-squared	0.69	0.7	0.72	0.73
Observations	191	191	191	191

Robust standard errors in parentheses

* significant at 10% level; ** significant at 5% level *** significant at 1% level

Appendix A- Interview Protocol

Interview Protocol 1 (see Phillips and Fernandes, 2003)

1. **Firm History**
    a. *When was the firm founded and when was it incorporated?*
    b. *Why did you decide to start this firm?*
    c. *Did you begin with a written business plan?*
    d. *How many employees do you currently have and can you describe how your organization is structured?*
    e. *What are your current revenues and how fast are you growing?*
2. **The Entrepreneurial Process**
    a. *Is this your first entrepreneurial venture?*
    b. *Tell me about the process of raising capital. What were your biggest strengths? Weaknesses?*
    c. *Tell me about your experience identifying potential partners and suppliers?*
    d. *What are the reasons you think that your firm can exploit this entrepreneurial opportunity better than large, established firms or your competitors?*
    e. *What type of work experience do you value in hiring potential employees?*
3. **The Parent Firm**
    a. *Where did you work immediately prior to this venture? How long were you employed there? Why did you decide to leave?*
    b. *How would you describe the corporate culture of your previous employer and how does it differ from your current venture?*
    c. *Does your firm compete directly or indirectly with your old firm?*
    d. *How does your management of R&D differ from your previous employer?*
    e. *In your opinion, what are the most crucial factors in identifying entrepreneurial opportunities in medical device?*
4. **Intellectual Property and Regulatory Process**
    a. *How many products does the firm have?*
    b. *How many patents does the firm currently have and when were they granted?*
    c. *Were the inventors ever employed by your firm and if so, are they currently employed by your firm?*
    d. *Where and when were the patented innovations first conceived?*
    e. *Do your patents cite older patents from your previous employer? If so, why did you choose to commercialize this invention through a new firm rather than an established firm?*
    f. *Could this innovation be developed in a large company? Why or why not?*
    g. *How many times have you gone through the FDA approval process at your current firm? How important was your prior experience in managing this process?*
    h. *Did you outsource the FDA approval process or handle it in-house?*
    i. *Does your device qualify for Medicare reimbursement?*
    j. *On a scale of 1-7, could you rate the following sources of innovation in the medical device industry, with 1 being insignificant and 7 being extremely critical?*
    1) University Research 2) Practicing Physicians 3) Medical device manufacturers 4) Medical device firm research and development employees
    k. *Is there anything else you think is important about the entrepreneurial process in the medical device industry that you would like to share?*
    l. *Are there other entrepreneurs in medical device that you think may be interesting for me to interview?*

Appendix B- Venture Capital in Medical Device historical data

Figure 1: Venture Capital Investments in Medical Device Industry 1995-2004
Source: PWC MoneyTree

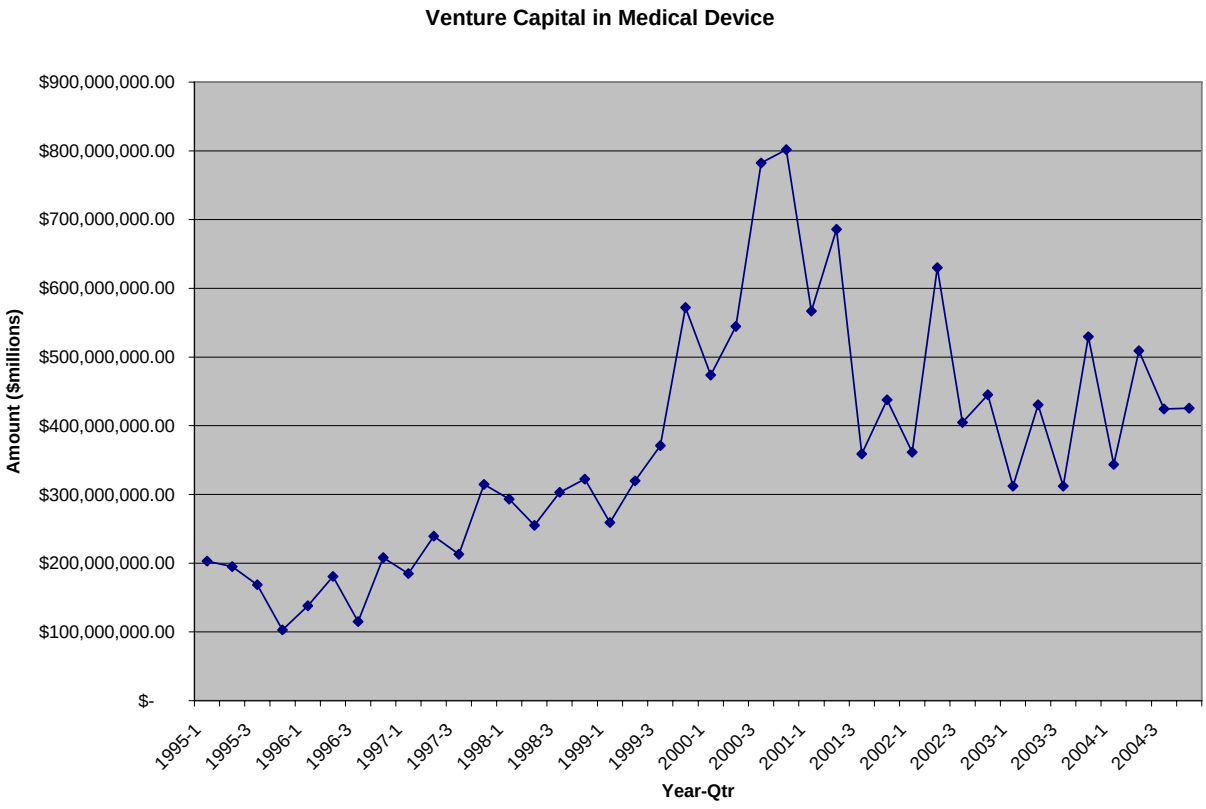

Figure 2: Venture Capital Deals in Medical Device Industry 1995-2004
Source: PWC MoneyTree

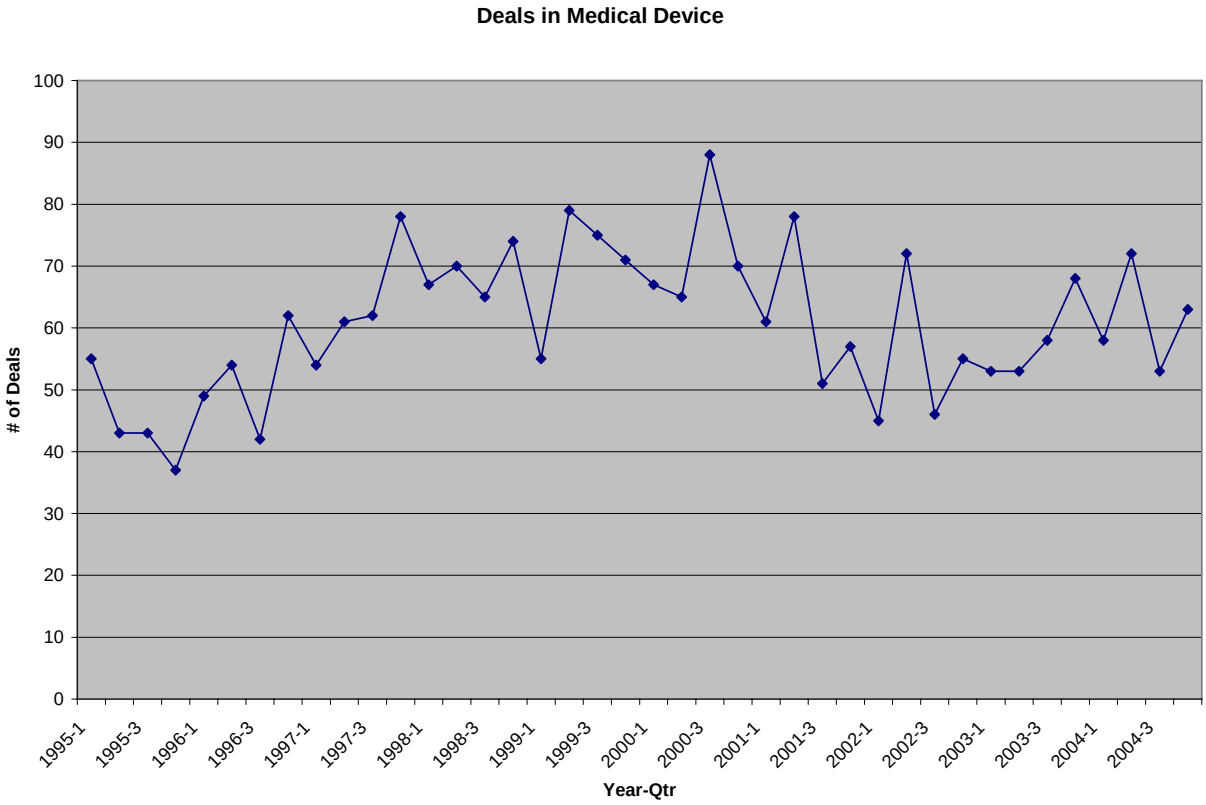

Figure 3: Venture Capital Investments Across All Industries (2004-Q2)

Industry	Amount	% of Total	# of Deals
Software	$1187M	20.22%	213
Biotechnology	$1009M	17.19%	89
Telecommunications	$516M	8.79%	61
Networking and Equipment	$513M	8.74%	46
Semiconductors	$505M	8.60%	59
Medical Devices and Equipment	$482M	8.22%	70
Media and Entertainment	$353M	6.02%	38
Computers and Peripherals	$239M	4.06%	36
Industrial/Energy	$206M	3.51%	38
Business Products and Services	$194M	3.30%	33
Electronics/Instrumentation	$185M	3.15%	23
IT Services	$174M	2.96%	36
Healthcare Services	$151M	2.57%	18
Financial Services	$118M	2.01%	17
Retailing/Distribution	$33M	0.56%	10
Consumer Products and Services	$6M	0.11%	7

Source: PWC MoneyTree

Figure 4: Medical Device Venture Capital Investments by Region (2004-Q2)

Region	Amount	% of Total	Deals
Silicon Valley	$234M	48.47%	21
San Diego	$82M	16.97%	8
New England	$35M	7.32%	6
North Central	$30M	6.23%	4
Northwest	$29M	6.01%	3
LA/Orange County	$19M	4.01%	3
Midwest	$19M	3.86%	6
Southeast	$14M	3.00%	4
Texas	$10M	2.03%	3
Colorado	$5M	0.94%	2
DC/Metroplex	$2M	0.49%	3
Philadelphia Metro	$2M	0.45%	3
NY Metro	$1M	0.19%	3
Upstate-NY	$0M	0.04%	1

Source: PWC MoneyTree