Strategic Management Journal
Strat. Mgmt. J., **30**: 185–206 (2009)
Published online 22 September 2008 in Wiley InterScience (www.interscience.wiley.com) DOI: 10.1002/smj.729
Received 23 February 2007; Final revision received 30 July 2008

SPAWNED WITH A SILVER SPOON? ENTREPRENEURIAL PERFORMANCE AND INNOVATION IN THE MEDICAL DEVICE INDUSTRY

AARON K. CHATTERJI*
Fuqua School of Business, Duke University, Durham, North Carolina, U.S.A.

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 strategy, economics, and organizational sociology, I assess the impact of 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, but rather by nontechnical knowledge related to regulatory strategy and marketing. Copyright © 2008 John Wiley & Sons, Ltd.

INTRODUCTION

None of the skeptical colleagues attending his poster session at the November, 1976 American Heart Association meeting in Miami, Florida, realized that Dr. Andreas Gruentzig was about to make a presentation that would eventually revolutionize medicine. Gruentzig, a German-born physician, described his offbeat idea to use a balloon catheter to clear blocked coronary arteries, thus delivering oxygenated blood to the heart; a procedure called angioplasty (Angioplasty.org, 2005). John Simpson, a recent graduate of the Stanford Medical School, who attended another Gruentzig presentation at Stanford, was, like most, impressed, yet unconvinced about the balloon method. However, while participating in an unsuccessful routine coronary angiogram, Simpson realized that the patient may have been helped had the Gruentzig method been used. To learn more about this new procedure, Simpson went to Europe to visit Gruentzig and in 1978 founded Advanced Cardiovascular Systems, a successful medical device company that helped create an entirely new specialty within medicine and spawned numerous other medical device firms through its former employees (Cassak, 2003). The entrepreneurial culture at Advanced Cardiovascular Systems, later described as the 'university of medical devices'[1], produced the next generation of medical device start-ups that would later commercialize several important medical technologies.

In fact, entrepreneurship in many high-technology industries often occurs through 'spawning' (Garvin, 1983; Gompers, Lerner, and Scharfstein, 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. Employment at an incumbent

Keywords: spin-offs; entrepreneurship; innovation; knowledge flows; medical devices; technology
*Correspondence to: Aaron K. Chatterji, Fuqua School of Business, Duke University, 1 Towerview Road, Durham, NC 27708, U.S.A. E-mail: ronnie@duke.edu

[1] Quote from interview conducted by the author with ACS employee.

Copyright © 2008 John Wiley & Sons, Ltd.

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 start 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.[2]

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 study, I will investigate whether entrepreneurial spawns perform better than their competitors and assess the extent to which 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 strategy, economics, and organizational sociology. I use this prior work to develop four testable hypotheses and then provide a brief overview of the medical device industry and explain why it is well suited for this study. The following section describes the dataset and how it was constructed. I then present the major results on performance and knowledge inheritance. Finally, I offer my conclusions and outline the major caveats to this analysis in the last section.

THEORETICAL FRAMEWORK AND HYPOTHESES

Prior employment and entrepreneurial opportunities

While the romantic (and popular) notions of entrepreneurship conjure up images of a college dropout working out of his parents' garage on the next big thing, most entrepreneurs have significant prior employment experience (Cooper, 1985; Cooper and Dunkelberg, 1986; 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 had come 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 the 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.

Other scholars have empirically studied why some firms spawn more new ventures than others. Gompers *et al*. (2005) test 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 and Bower 1996) and internal capital budgeting may favor ongoing projects instead of innovative ideas. Thus, entrepreneurial employees, frustrated with an employer's reluctance to prioritize innovation and exploit new opportunities, will leave the firm to start their own venture. Interestingly, this phenomenon is one explanation for where the capabilities of new entrants come from. (Klepper and Simons, 2000)

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

Copyright © 2008 John Wiley & Sons, Ltd.

Gompers and his coauthors (2005) 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 venture capital 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 (2005) 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?' (Gombers *et al.*, 2005: 613).

Similarly, Burton, Sørensen, and Beckman (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...' (Burton *et al.*, 2002 :39).

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 interorganizational affiliation proposed in Stuart, Hoang, and Hybels (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 interorganizational endorsements will reduce the uncertainty surrounding young firms and allow third parties to make more informed judgments about new ventures.

Thus, as discussed in detail above, prior work in strategy, economics, and organizational sociology suggests that spawns of large, prominent, entrepreneurial 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 interorganizational affiliations 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 (Hsu 2004b). Hsu (2004a) finds that 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 an entrepreneur 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

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

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:

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 implication of Klepper and Sleeper (2005) 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) find 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 (nonpublic) 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.

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 customers. 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 (2005) and Gompers *et al.* (2005)) where spawns use knowledge cultivated at the parent firm to exploit entrepreneurial opportunities?

As suggested by Klepper and Sleeper (2005) 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.[3]

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. Moreover, spawns inherit technical and marketing know-how from their parents, and these capabilities will enhance spawn survival.

However, it is difficult to trace the inheritance of this technological and marketing know-how across firms. In this study, I will focus on technological knowledge in my empirical models and gain insights on other types of knowledge through interviews and the review of industry research. Preliminarily, I examine the relationships between parent and spawn patent portfolios. Therefore, I propose:

[3] Klepper and Sleeper (2005) make an interesting point that this relationship may be nonmonotonic.

Copyright © 2008 John Wiley & Sons, Ltd.

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

The medical device industry

New medical technologies and devices are increasingly 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 Advanced Cardiovascular Systems alums, serial entrepreneurs who found multiple companies, and individuals from outside the industry who develop promising ideas.

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 Computerized Axial Tomography (CAT) scan machines, therapeutic devices such as pacemakers and surgical instruments like endoscopes. Products are usually marketed and sold directly to health care 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 (AdvaMed, 2004; PricewaterhouseCoopers [www.pwcmoneytree.com, accessed 1 March, 2005]).

The U.S. 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.[4] 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 Francisco Bay Area, Minneapolis, Orange County, CA, and Boston, allowing for considerable employee mobility since individuals can easily change jobs without relocating.[5]

Additionally, patenting is crucial in the medical device industry with over 9,000 patents issued by 2003. Patenting of medical devices is usually considered a crucial part of firm strategy in this sector.[6] Furthermore, academic research is a key component of product development. In many cases, advances in the academic literature spur product development and company formation.[7] 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 two 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 two quarters of 2004.[8]

DATA AND METHODS

Data sources

To answer the research questions posed above, I utilize four major data sources; 1) the Dow Jones Financial Information Services' VentureOne (VentureSource) online database; 2) Thomson Financial Venture Economics's Venture Xpert database; 3) National Bureau of Economic Research (NBER) patent database; and 4) Semi-structured interviews with medical device entrepreneurs.

VentureOne and Venture Xpert have been used by many scholars to investigate issues surrounding venture capital and private companies (Kaplan, Sensoy, and Stromberg, 2002). VentureOne was established in 1987 and tracks firms that have

[4] This study addresses the medical device industry in the United States only.

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

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

[7] The birth of 'Hypothermia companies' between 1996–1998 was partly based on advances in research on cooling the human body.

[8] This statistic is according to the Dow Jones Financial Information Services' VentureOne, VentureSource online database.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

received venture capital financing. The firms are identified through trade press, company Web sites, 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 VentureOne dataset.

The NBER patent database has data on nearly three million U.S. patents granted between 1963 and 1999 (Hall, Jaffe, and Trajtenberg, 2001). I used medical device patents and citations to analyze innovation among entrepreneurial ventures and incumbents in the industry. Through industry contacts, I conducted interviews with CEO/Founders of privately held medical device companies in my data. The purpose of the interviews was to gain insights into 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 telephone and in person, ranging from about thirty minutes to three hours. If the interviewee agreed, the conversations were also recorded. In developing the interview protocol, I relied on Phillips and Fernandes (2003), where the authors conducted interviews of entrepreneurs in the professional services area. Please see Appendix A for details of the interview protocol.

Building the dataset

I use VentureOne 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 1,000 firms. For each firm, I 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.[9]

Constructing measures

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 VentureOne 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 VentureOne 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 possible, but may not indicate the true age of the firm. Next, neither VentureOne 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 financed by angel investors. In practice however, most successful medical device companies receive venture capital funding, and data on non-venture capital backed medical device companies is not readily available.[10]

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

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

[10] 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.

Copyright © 2008 John Wiley & Sons, Ltd.

sample received at least one round of venture capital funding, there exists some common metrics of performance across each of the 191 firms.

I use 'pre-money' valuation, or the valuation of the company (as determined by investors at rounds of nonpublic financing), as one measure of performance in this study. Market valuation is a common measure of performance in the strategic management literature (see Villalonga, 2004 for one example) and different measures of pre-money valuation have been used in several previous studies (Lerner, 1994; Stuart *et al*., 1999; Higgins and Gulati, 2003; Hsu, 2004b). 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 (Levine, 2001).

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 two 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.

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 Advanced Cardiovascular Systems, Medtronic, Baxter, and 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 large medical device firms earlier in their careers.

Therefore, I define a spawn as an individual who at some point in his 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 that have at least one individual who worked at any point in his career at a publicly traded medical device or pharmaceutical/biotechnology firm are considered 'spawns' for the purpose of this 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.[11]

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 the 'parent' for the purposes of this study. Next, VentureOne does not have data on what date the individual joined the entrepreneurial venture, so I conducted my own research (interviews, Lexis-Nexis, company Web site searches) to determine whether the individual is actually the entrepreneur, or an employee who joined later on. In almost all

[11] 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.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

cases, I am able to precisely determine the founder of the company and where he or she worked previously, but it is possible that a cofounder has been omitted in some cases.

Through the information in VentureOne and my own research, I classify each of the non-spawn founders into three 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. 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 it could alternatively be called 'academic/nonprofit researcher'). Finally, if the founder has previously worked only outside the industry, I code the venture as having an outsider founder. With these three additional categories and the previously discussed spawn category, I have classified all of the founders in my sample into four broad categories.

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 VentureOne. 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. Furthermore, I control for whether the venture has received corporate venture capital, which provides an additional source of capital and connections to potential alliance partners and acquirers (Dushnitsky and Lenox, 2005).[12] Finally, I also introduce controls that capture the venture's stage of development, since venture capitalists assess various milestones in estimating firm valuation. Whether the firm has existing customers, an international distribution channel, a co-marketing agreement, or has contracted with an original equipment manufacturer (OEM) are all favorable signs that the firm will be successful. I control for each of these milestones using dummy variables in the analysis.

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

RESULTS

Empirical strategy

I first use the data from VentureOne 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 nontechnical knowledge in spawning.

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 seven years. Thus, the sample is composed of small, young medical device firms, and the distribution of the dependent variable is highly skewed.[13]

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 with no past entrepreneurial experience (29%), 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.[14]

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 nine ventures in my sample, going back to its days as Advanced Cardiovascular Systems.

[13] 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. Ninety percent90% of firms in the sample have less than 50 employees.

[14] 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.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

Table 1. Descriptive statistics

Variable	N	Mean	S.D.	Min	Max
First round pre-money valuation (MM)	191	6.40	6.60	0	39.30
Last round pre-money valuation (MM)	191	40.40	62.00	0.50	499.00
Spawn	191	0.36	0.48	0	1.00
Serial	191	0.25	0.43	0	1.00
Physician	191	0.29	0.46	0	1.00
Outsider	191	0.09	0.29	0	1.00
Age(yrs)	191	6.70	2.90	0.67	18.90
Financingrounds	191	4.70	2.40	1.00	13.00
CorporateVC	191	0.14	0.34	0	1.00
OEM	191	0.07	0.26	0	1.00
GenDistr	191	0.13	0.34	0	1.00
CoBrdMkt	191	0.05	0.22	0	1.00
GlobalDistr	191	0.09	0.29	0	1.00
JointRD	191	0.06	0.23	0	1.00
Customer	191	0.10	0.30	0	1.00

Table 1A. Top spawners in the medical device industry

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

Regression results

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

$$Time\ toFunding = F\ (Spawn,\ Serial,\ Year,\ Industry\ Segment) \tag{1}$$

$$Valuation = F\ (Spawn,\ Serial,\ Year,\ Industry\ Segment,\ Round,\ Firm\ Controls) \tag{2}$$

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, supporting Hypothesis 1.[15] 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 one-year 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 submarket. I will discuss the implications of this result further below.[16]

In Table 3, my results demonstrate that spawns achieve higher valuations at the last round of

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

[16] As a robustness check, I employed a piecewise exponential model and found very similar results.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

Table 2. Regression estimates of determinants of time to funding

Variable	(1)	(2)	(3)
Spawn	−0.967***	−0.689**	−0.563*
	(0.255)	(0.267)	(0.312)
Serial	−1.08***	−0.740**	−0.522*
	(0.282)	(0.289)	(0.302)
Constant	6.027	6.31	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
Notes: Excluded groups are physicians and outsiders. Negative sign indicates faster time to funding. Thus, spawns are funded more quickly than physicians and outsiders.

financing, supporting Hypothesis 2a. 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. The results are consistently significant at the five percent level until firm-level control variables are introduced in the last specification. At that point, the results are still significant at the 10 percent level. With only 191 firms and controlling for founder characteristics, round, industry segment, and financing year, this is not surprising.[17] 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 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 the 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.

Patent analysis

The empirical results suggest that spawns perform better than other entrants. What accounts for the

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

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
Notes: Excluded groups are physicians and outsiders. Positive sign indicates higher valuation. Thus, spawns receive higher valuations than physicians and outsiders.

Copyright © 2008 John Wiley & Sons, Ltd.

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 two broad questions:

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?

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.[18]

Of the 191 firms with financing information available, 69 are classified as spawns. Examining these 69 firms, I first calculate which patent class (International Patent Classification [IPC]) 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.[19] Overall, the parent firms have 78 percent of their patents in three classes.

Out of the 69 spawned ventures, six (8%) have the statistical majority of their patents in their parent firm's primary patent class. Of the 69 spawned firms, 23 (33%) have the majority of their patents in one of the top three patent classes for their parent. These descriptive statistics imply that not all spawns patent in the same patent classes as the parent firm.[20] 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.[21]

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, Trajtenberg, and Henderson (1993) provide a longer discussion about the merits of using patent citations as a measure of technical spillovers.

Of the 69 spawned firms in my data, 12 cite the parent firm, and the average citation rate (number of cites to parent/number of total cites) for citing firms is three percent. Of course, the overall citation rate to the parent firm is very low for spawns, around one percent 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 Vascular Engineering (not in the financing sample) devoting more than 10 percent 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

[18] In the Klepper and Sleeper (2005) model framework, we might view the knowledge that former employees retain from their parent firm to be most useful in technologically related areas.

[19] To do so, I divide the parent firm's patent portfolio by class and identify the three classes with the most patents.

[20] This fact does not preclude the spawn from working in the same product area as the parent, but makes it less likely.

[21] Twenty-two spawned ventures did not have issued patents as of 1999.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

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 nontechnical 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 nontechnical founders. If the founders have a doctor of medicine degree, a science graduate degree, or any patents, I characterize them as a technical founder. Of of the 69 spawns, 46 have technical founders—I included a dummy variable for this in the regressions that follow and my results changed very little.

Creating a benchmark

The results from the patent analysis reveal that spawns devote one percent 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, spawns 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.[22],[23]

To address some of these concerns, I create a control set of patents for the spawn patents based on application year, IPC four-digit class, and grant year.[24] For each of the 792 spawn patents, I identify a control patent that has the same application year, same IPC, 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.[25]

Appendix C presents the top 10 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.[26] 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 percent. 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 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 0.00906 or 0.906 percent.

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 percent. 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.

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

[22] In other words, we must know how much other non-spawn firms are citing the parent firm's patents to properly evaluate the citation rates from the spawn to the parent. If the spawn is citing the parent firm as much as other non-spawn firms, even a high citation rate may not indicate inheritance from technological spillovers.

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

[24] 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.

[25] 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 the 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.

[26] 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.

Copyright © 2008 John Wiley & Sons, Ltd.

my dataset 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 two cases.

Case 1) The founder is the inventor on the citing patent (the spawn patent) and listed on the cited patent (the parent patent).
Case 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 found 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 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. Eighteen citations are Case 1 types where the founder is on both the citing and the cited patent, and 20 citations are Case 2 types where the founder is not on the citing patent but is on the cited patent. 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 percent, 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?

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 four 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 did patent predominantly in one of their parent's top three classes), Spawn Simple (for those spawned firms that did not cite their parent), and Spawn Tech Inheritor (for those spawned firms that did 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.[27] The purpose

[27] 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.

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

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
Notes: Excluded groups are physicians and outsiders. Positive sign indicates higher valuation.

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
Notes: Excluded groups are physicians and outsiders. Positive sign indicates higher valuation. Thus some spawns (those who do not inherit technical knowledge from their parent) receive higher valuations than physicians and outsiders.

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 that 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 nonpublic 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.[28] Thus, I find no support for the claim of Hypothesis 3 that spawns that inherit technical knowledge

[28] If anything, the evidence suggests that spawns that do not cite their parents have higher valuations.

Copyright © 2008 John Wiley & Sons, Ltd.

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.

$$\begin{aligned} &Pr\ (Product\ Approved = 1) \\ &\quad = F\ (Spawn\ Unrelated,\ Spawn \\ &\quad Related,\ Serial,\ Year,\ Industry \\ &\quad Segment,\ Round,\ Firm\ Controls) \quad (3) \end{aligned}$$

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 parents) seem to outperform their competitors in terms of obtaining FDA approval. Table 7 presents results of a hazard specification that allows for censoring. We see that spawns that are working in related areas to their parents get products approved by the FDA faster.

These results indicate that spawns that 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?

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)
Financing rounds	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

Notes: Excluded groups are physicians and outsiders. Positive sign indicates higher likelihood of FDA approval. Thus, spawns in related technology areas to their parent are more likely to get products approved by the FDA than physicians and outsiders.

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% level

Note: Positive sign indicates quicker time to product approval. The excluded groups are physicians and outsiders. Thus, spawns in related technology areas to their parent obtain FDA approval more quickly than physicians and outsiders.

These spawns that 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 nontechnical knowledge below.

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 that 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.

Copyright © 2008 John Wiley & Sons, Ltd.

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 nontechnical 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 members 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 $20 million (Snowbeck, 2006). 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 (*IN VIVO*, 2004). Former employees of large medical device firms who have managed clinical trials often have crucial knowledge that can speed up the approval process.

Furthermore, the process of obtaining coverage from Medicare to reimburse the use of a medical device is also critically important and complicated for a medical device firm. In fact, many device firms now employ a full-time executive to navigate the process, which can take between one to five years (Radinsky, 2004). Private insurers usually look for guidance from Medicare when deciding to reimburse a device, so Medicare's decision is often pivotal in spurring widespread adoption of a medical device. Potential venture capital investors may also require a detailed reimbursement strategy as a precondition for investment. Thus, providing the Centers for Medicare & Medicaid Services (CMS) with a persuasive case for reimbursement is a priority for a medical device start-up. CMS evaluates whether the device improves patient outcomes over existing technologies, in contrast to the FDA, which focuses on safety. Prior experience navigating this process is once again crucial to success.

Importantly, interviewees also stressed the importance of prior experience in identifying entrepreneurial opportunities. Employees at large device firms 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, prior experience marketing products to physicians provided valuable insight into what new devices might look like and who might buy them. One interviewee mentioned his experience in sales and marketing at Johnson & Johnson as being an important component of his later entrepreneurial success since he had been exposed to a wide range of products in the health care industry and was familiar with all of the prominent stakeholders.

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, where venture capitalists are active.

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 (Levin, 2002: 51)

Interestingly, when Hooven left in 1994 to start his own company, he did not know exactly what

Copyright © 2008 John Wiley & Sons, Ltd.

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 (Levin, 2002). His experience at Johnson & Johnson had helped him identify new entrepreneurial opportunities, rather than a specific technical idea.

Finally, it is worth noting that interviewees also mentioned the difficulties, not just the advantages, of founding a new venture after working at a large industry incumbent. Two CEOs noted that managers at large firms are used to several layers of hierarchy, where checks and balances are firmly in place, and where specialization is highly valued. In contrast, entrepreneurial firms require general management skills, because of the lack of formal roles and hierarchy, and start-ups lack the accountability measures of a large firm.

In sum, my results suggest that spawns do perform better than other entrants, but that technological knowledge inheritance is not the major reason. Instead, nontechnical 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 the medical device field, it would seem that these types of knowledge are more important.

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 study, I analyze performance and technical knowledge inheritance for spawns in the medical device industry. In support of Hypothesis 1, I find that spawns do obtain funding more quickly than their competitors (excluding serial entrepreneurs). I also find support for Hypothesis 2a, that spawns receive higher valuations at the last round of funding, compared to other entrants. These results imply that spawns perform better than other entrants, a finding that has been documented in the prior literature. As previously mentioned, Hypothesis 2b, that posits entrepreneurial ventures that have been spawned by incumbent firms in the industry will be more likely to commercialize a product than other entrants, is not supported. Interestingly, only those spawns that are most related to their parent (in terms of their choice of what technological areas to enter) obtain FDA approval more quickly than other firms.

Most interestingly though, as noted earlier, I find little evidence to support Hypothesis 3, 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 nontechnical 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. Moreover, the particular type of knowledge present in the external environment could have implications for the performance of entrepreneurial start-ups, and this issue should be explored in future research (Sarkar *et al.* 2006).

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 VentureOne, Venture Xpert, and my own research, which may be biased by unobserved trends. To mitigate this,

Copyright © 2008 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

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.

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. 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.[29]

There are several interesting research questions to pursue based on the results of this study 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 interorganizational affiliation and prominence. In particular, it would be useful to understand what variables mediate the impact of interorganizational 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? How does the length of job tenure or the amount of time that has passed since leaving the parent firm impact the success of spawns?[30]

Furthermore, it would be interesting to attempt to further differentiate between various kinds of parent firms, similar to what Gompers *et al*. (2005) identify with respect to Xerox- and Fairchild- type firms. After all, parent firms could be classified into several different categories, based on size, prominence in the industry, entrepreneurial culture, and other characteristics. While prior work has provided evidence that some firms spawn more than others, there is more work to be done in comparing the performance of spawns based on the characteristics of their parent firm. For example, the few spawns that do arise from Xerox-type firms may be interesting candidates for future study.

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. Spawned entrepreneurs with prior entrepreneurial experience are interesting candidates for further research, since they presumably embody much of the valuable technical, industry-specific, regulatory, and managerial knowledge (taken together to embody 'the silver spoon') necessary to launch successful entrepreneurial ventures.

ACKNOWLEDGEMENTS

I am grateful to Rajshree Agarwal, Waverly Ding, John Freeman, Bronwyn Hall, Steven Klepper, David Levine, David Mowery, Christopher Rider, Jason Snyder, David Teece, Catherine Wolfram, and the students at the Business and Public Policy Student Seminar and the Innovation Workshop at the Haas School of Business, UC-Berkeley. This research is supported by the Ewing Marion Kauffman Foundation. I also wish to thank Evan Anderson, Kirsten Armstrong, and many other medical

[29] 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.

[30] Thank you to an anonymous reviewer for posing this question.

Copyright © 2008 John Wiley & Sons, Ltd.

device entrepreneurs, venture capitalists, and engineers who have contributed to my understanding of this industry. All mistakes are my own.

REFERENCES

AdvaMed. 2004. *Annual Report*. Advanced Medical Technology Association: Washington, D.C.

Agarwal R, Echambadi R, Franco A, Sarkar MB. 2004. Knowledge transfer through inheritance: spin-out generation, development, and survival. *Academy of Management Journal* **47**(4): 501–522.

Almeida P, Kogut B. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(7): 905–917.

Angioplasty.org. 2005. Interview with Richard K. Myler. Angioplasty.org. www.ptcs.org/nv/interviews/index.html (4 April 2005).

Anton JJ, Yao DA. 1995. Start-ups, spin-offs, and internal projects. *Journal of Law, Economics, and Organization* **11**: 362–378.

Bhide A. 1994. How entrepreneurs craft strategies that work. *Harvard Business Review* **72**(2): 150–161.

Brittain JW, Freeman J. 1986. Entrepreneurship in the semiconductor industry. Working paper, University of California Berkeley.

Burton MD, Sørensen J, Beckman CM. 2002. Coming from good stock: career histories and new venture formation. In *Social Structure and Organizations Revisited (Research in the Sociology of Organizations)* (Vol. 19), Lounsbury M, Ventresca M. (eds). JAI Press/Elsevier: Oxford, UK; 229–262.

Cassak D. 2003. John Simpson: Reluctant Entrepreneur. *In Vivo, The Business & Medicine Report* **21**(4): Available at http://www.denovovc.com/press/denovo-simpson.pdf.

Christensen CM, Bower JL. 1996. Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal* **17**(3): 197–218.

Cooper AC. 1985. The role of incubator organizations in the founding of growth-oriented firms. *Journal of Business Venturing* **1**(1): 75–86.

Cooper AC, Dunkelberg WC. 1986. Entrepreneurship and paths to business ownership. *Strategic Management Journal* **7**(1): 53–68.

Cooper AC, Dunkelberg WC, Woo CY, Dennis WJ Jr. 1990. *New Business in America: The Firms & Their Owners.* The NFIB Foundation: Washington, DC.

Dushnitsky G, Lenox MJ. 2005. When do firms undertake R&D by investing in new ventures? *Strategic Management Journal* **26**(10): 947–965.

Garvin DA. 1983. Spin-offs and the new firm formation process. *California Management Review* **25**(2): 3–20.

Gompers P, Lerner J, Scharfstein D. 2005. Entrepreneurial spawning: public corporations and the genesis of new ventures, 1986 to 1999. *Journal of Finance* **60**(2): 517–614.

Hall BH, Jaffe AB, Trajtenberg M. 2001. The NBER patent citation data file: lessons, insights and methodological tools. Working Paper 8498, National Bureau of Economic Research, Cambridge, MA.

Hellmann T. 2002. When do employees become entrepreneurs? Working paper 1770, Stanford Graduate School of Business, Stanford University, Stanford, CA.

Higgins M, Gulati R. 2003. Getting off to a good start: the effects of upper echelon affiliations on underwriter prestige. *Organization Science* **14**(3): 244–263.

Hsu D. 2004a. Experienced entrepreneurial founders, social capital, and venture capital funding. Working paper, Wharton School of Business, University of Pennsylvania, Philadelphia, PA.

Hsu D. 2004b. What do entrepreneurs pay for venture capital affiliation? *Journal of Finance* **59**(4): 1805–1844.

IN VIVO Business and Medicine Report. 2004. Emerging Company Profiles: Cardiovascular device companies: Acorn Cardiovascular, AFx, CardioVasc. *IN VIVO* **18**(2): 12.

Jaffe AB, Trajtenberg M, Henderson R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* **108**(3): 577–598.

Kaplan SN, Sensoy BA, Stromberg P. 2002. How well do venture capital databases reflect actual investments? Working Paper, University of Chicago Graduate School of Business, Chicago, IL.

Klepper S. 2001. Employee startups in high-tech industries. *Industrial and Corporate Change* **10**(3): 639–674.

Klepper S, Simons KL. 2000. Dominance by birthright: entry of prior radio producers and competitive ramifications in the U.S. television receiver industry. *Strategic Management Journal*, October–November Special Issue **21**: 997–1016.

Klepper S, Sleeper S. 2005. Entry by spin-offs. *Management Science* **51**(8): 1291–1306.

Lerner J. 1994. The importance of patent scope: an empirical analysis. *RAND Journal of Economics* **25**(2): 319–333.

Levin S. 2002. Atricure: making order out of chaos. *IN VIVO Business and Medicine Report* **20**(3): 51–59.

Levine SD. 2001. Business valuation issues related to start-up companies. http://www.docstoc.com/docs/13 395/Business-Valuation-Issues-Related-to-Start (20 April 2005).

Phillips D. 2002. A genealogical approach to organizational life chances: the parent-progeny transfer among Silicon Valley law firms, 1946–1996. *Administrative Science Quarterly* **47**: 474–506.

Phillips D, Fernandes G. 2003. Network based entrepreneurship: an interview-based investigation of professional service firm start-ups. Working paper. Polsky Center for Entrepreneurship, University of Chicago Graduate School of Business, Chicago, IL.

Radinsky G. 2004. Preventing coverage delays is key to device profits. *Medical Device & Diagnostic Industry* 2004(January): 142–147.

Copyright © 2008 John Wiley & Sons, Ltd.

Robinson PB, Sexton EA. 1994. The effect of education and experience on self-employment success. *Journal of Business Venturing* **9**(2): 141–156.

Sarkar MB, Echambadi R, Agarwal R, Sen B. 2006. The effect of the innovative environment on exit of entrepreneurial firms. *Strategic Management Journal* **27**(6): 519–539.

Snowbeck C. 2006. 'Heart Sock' dealt third setback: FDA vote means Acorn must spend millions on studies. *Saint Paul Pioneer Press*, St. Paul, MN. 16 December 2006.

Stuart TE, Hoang H, Hybels R. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* **44**(2): 315–349.

Villalonga B 2004. Intangible resources, Tobin's q, and sustainability of performance differences. *The Journal of Economic Behavior & Organization* **54**(2): 205–230.

Copyright © 2008 John Wiley & Sons, Ltd.

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 the medical device industry?*

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 devices that you think may be interesting for me to interview?*

APPENDIX B: WEB SITES CONSULTED FOR DATA COLLECTION

Angioplasty.Org
http://www.ptca.org; Last accessed 4 April 2005
Cath Lab Digest
http://www.cathlabdigest.com; Last accessed 10 September 2005
PriceWaterhouseCoopers Money Tree
http://www.pwcmoneytree.com; Last accessed 10 September 2005
Riverwest Venture Partners
http://www.rivervest.com; Last accessed 6 September 2005
The Cleveland Clinic
http://www.clevelandclinic.org; Last accessed 12 April 2005
The Motley Fool

Copyright © 2008 John Wiley & Sons, Ltd.

http://www.fool.com; Last accessed 12 April 2005
Windhover Information Inc.
http://www.windhover.com; Last accessed
10 September 2005

APPENDIX C: PATENT ANALYSIS

	Spawn	Control
Total number of patents	792	712
Top ten cited orgs	Target Therapeutics, Inc.	Advanced Cardiovascular Systems, Inc.
	Cordis Corporation	Medtronic Inc.
	Advanced Cardiovascular Systems, Inc.	United States Surgical Corporation
	Devices for Vascular Interventions	Cordis Corporation
	Olympus Optical Co; Ltd	Olympus Optical Co; Ltd
	Sci-Med Life Systems, Inc.	Everest Medical Corporation
	Medtronic, Inc.	3M
	Danek Medical, Inc.	Baxter International Inc.
	Cardiovascular Imaging Systems, Inc.	ValleyLab, Inc.
	Cook Inc.	General Electric Company
Citation rate to parent	1.040%	0.906%

Copyright © 2008 John Wiley & Sons, Ltd.