RAND Journal of Economics
Vol. 37, No. 4, Winter 2006
pp. 841–860

Spin-outs: knowledge diffusion through employee mobility

April Mitchell Franco*

and

Darren Filson**

In many industries, one important method of diffusion is through employee mobility: many of the entering firms are started by employees from incumbent firms using some of their former employer's technological know-how. This article explores the effect of incorporating this mechanism in a general industry framework by allowing employees to imitate their employers' know-how. The equilibrium is Pareto optimal because the employees "pay" for the possibility of learning their employers' know-how. The model's implications are consistent with data from the rigid disk drive industry. These implications concern the effects of know-how on firm formation and survival.

1. Introduction

■ The transmission of knowledge between firms often occurs through employee mobility. New firms are often spin-outs, firms started by a former employee of an incumbent firm. This has been observed in the automobile and construction industries, as well as among advertising agencies and law firms (Garvin, 1983; Phillips, 2003). Spin-outs are the most important type of entrant in many high-tech industries, where technological know-how is often embodied in human capital. Braun and Macdonald (1982) and Christensen (1993) document the importance of spin-outs in the semiconductor and rigid disk drive industries, two generic examples of high-tech industries.

Existing models of industry evolution, such as Gort and Klepper (1982) and Jovanovic and MacDonald (1994a, 1994b), do not specify the mechanism through which knowledge diffuses. Here, we introduce a model that specifies a mechanism: employees can attempt to imitate their employers' know-how and use it to start their own firms. Each period, each agent can either work outside the industry, work as a researcher in the industry, or run a firm. In equilibrium, agents with sufficiently high know-how run firms. Other agents can work in the industry to attempt to

* University of Iowa; april-franco@uiowa.edu.

** Claremont Graduate University; Darren.Filson@cgu.edu.

We thank Kelly Bedard, Robert Brown, Hal Cole, Nancy Gallini, Eric Helland, Tom Holmes, Hugo Hopenhayn, Narayana Kocherlakota, Francine Lafontaine, Glenn MacDonald, Matt Mitchell, Edward C. Prescott, two anonymous referees, participants at 1995 Winter Meetings of Society of Economic Dynamics and Control, 1999 Vigo Workshop in Dynamic Macroeconomics, 1999 Society for Economic Dynamics Meetings, 1999 Canadian Economics Association Meetings, and 1999 Western Economics Association Meetings, and seminar participants at Instituto y Universidad Torcuato di Tella, Federal Reserve Bank of Cleveland, Board of Governors, Simon School of Business, Federal Reserve Bank of Minneapolis, and Federal Reserve Bank of Richmond for their help in developing this article; Aida Budiman, Shubala Mani, and Bunchon Songsamphant for research assistance; and James Porter, editor of the *Disk/Trend Report*, for the data. All remaining errors are our own.

improve their know-how. Over time, as firms innovate and researchers imitate, the distribution of know-how improves and the critical level of know-how required to run a firm rises.

The model yields several testable hypotheses. First, more technologically advanced firms produce spin-outs. Because the critical level of know-how required to run a firm continues to increase as the industry evolves, a researcher who learns from a laggard may not acquire sufficient know-how to run a firm. Second, a firm's probability of surviving is increasing in its technological know-how. This result and the learning mechanism yield a third hypothesis: a spin-out's probability of surviving is increasing in its parent's know-how. These hypotheses are tested on the rigid disk drive industry. There is support for the model's results on spin-out generation and firm survival. We find that spin-out survival is more closely related to some forms of parent know-how than others.

We explain several other facts about the rigid disk drive industry using a simulation of the model. For example, Lerner (1997) establishes that in the 1970s and 1980s, while the industry was expanding, profits were low and rose as the industry matured, even though the price was steadily declining. During this time, technological laggards who were close behind the leaders tended to catch up to leaders, and laggards who were further behind were more likely to exit. Laggards occasionally surpassed leaders. The simulation matches these trends and explains how laggard "leapfrogging" can occur.

The model also yields an important welfare conclusion. In contrast to previous models of technological diffusion, despite the fact that technology *spills over* from incumbents to spin-outs, the competitive equilibrium is optimal. The employees "pay" for the possibility of imitating their employers' know-how, because imitation is locationally specific and the agents who benefit can be identified. In Jovanovic and MacDonald (1994a), imitation depends only on the distribution of know-how in the industry and not on the actions of the individuals. The lack of property rights creates an externality and a suboptimal equilibrium. The optimality result presented here is similar to that in Chari and Hopenhayn (1991). Unlike that model, here the arrival of new technology is endogenous and depends on actions undertaken by agents in the economy.

The model contributes to the literature on industry evolution and knowledge diffusion. The competitive framework we use is similar to Hopenhayn (1992) and Jovanovic and MacDonald (1994a). Higher know-how increases output, as in Lucas's span-of-control (1978). However, here agents can improve their productivity either by working as researchers and imitating or by running a firm and innovating. Researcher imitation has been analyzed by Pakes and Nitzan (1983), but they focus on monopoly and duopoly markets and on characterizing the optimal contract between the firm and the researcher. Our results are quite different. Instead of paying the researcher a higher salary in the following period to prevent him from becoming a competitor, the firm owner adjusts wages in the current period by taking into account the value of imitating her technology and allowing the employee to leave.

In recent work similar to ours, Klepper and Sleeper (2000) consider the case where employees may leave to start a firm in a differentiated-products market and test their model's implications using data from the laser industry. Their model builds on Hotelling-style models of firms locating along a line. In contrast, our model builds more directly on explicit models of industry evolution such as Jovanovic and MacDonald (1994a). Klepper and Sleeper (2000) find evidence that spin-outs inherit know-how from parents, as do we.[1] They also find evidence that more successful firms spawn more spin-outs. However, they measure success using longevity. In contrast, we use a direct measure of know-how and find evidence that higher know-how firms are more likely to spawn spin-outs. Other firm characteristics such as size and sales growth have no explanatory power in determining whether the firm generates a spin-out in a given year once we control for the firm's know-how. In our data, while several spin-out parents are large established firms, others are small high-tech startups themselves.

[1] In the finance literature, "spin-offs" are created when an existing firm creates new firms from one of its divisions. Since the new firms we study are independent startups, we avoid confusion by using the term "spin-out." In Klepper and Sleeper (2000) a "spin-off" describes what we denote as a "spin-out."

The article proceeds as follows: Section 2 describes the evolution of the rigid disk drive industry, Section 3 presents the model and theoretical results, Section 4 provides a simulation, Section 5 provides the empirical results, and Section 6 concludes. All formal proofs are in an Appendix on the authors' websites www.cgu.edu/pages/428.asp.

2. A brief history of the rigid disk drive industry

■ We refer the interested reader to Christensen (1993, 1997), Lerner (1997), and the *Disk/Trend Report*, an annual market research publication that focuses on the rigid disk drive industry, for more complete descriptions of the industry's history. The industry began in 1956 when IBM introduced the first rigid disk drive. Followers began entering in the 1960s and were of two main types. Captive producers, such as Burroughs, Control Data, and Univac, were vertically integrated computer manufacturers that produced drives for in-house use. Plug-compatible market (PCM) firms were independent drive producers that made drives that were plug-compatible with IBM's computers. PCM firms sold drives directly to users of IBM computers. Christensen (1993) reports that many of the early PCM firms were IBM spin-outs, including Century Data, Memorex, Pertec, and Storage Technology Corporation. When the minicomputer market began growing rapidly in the mid-1970s, an original equipment market (OEM) emerged. OEM firms served as either primary or secondary sources of drives for computer manufacturers.

Innovation and imitation in the disk drive industry occurred at an extremely rapid rate from 1956 to 1997 and took several forms. First, several advances in technical features improved capacities and access times. Second, several improvements in design and manufacturing techniques improved costs and reliability. Third, several architectural innovations occurred: drives with smaller diameters were introduced beginning with 8″ and 5.25″ drives in the late 1970s and continuing with 3.5″, 2.5″, and 1.8″ drives. When first introduced, the new drives served new buyers: 8″, 5.25″, 3.5″, 2.5″, and 1.8″ drives were first used in minicomputers, personal computers, portable computers, notebook computers, and smaller portable devices, respectively. In response to the profit opportunities generated from rapid technological change and market growth, net entry occurred. The number of firms continued to rise until the mid-1980s and then leveled off a short time before falling in the early 1990s (Lerner, 1997). The patterns for net entry and the number of firms are similar to those established in industries with new products by Gort and Klepper (1982).

□ **Spin-outs: importance and imitation.** Focusing on U.S. disk drive firms in the period 1976–1989, Christensen (1993) shows that while spin-outs were not the only source of entry, they were definitely the most important source. Only 3 out of 28 non-spin-out entrants survived until 1989, but 16 out of 40 spin-outs survived. Spin-outs accounted for all but four of the startups that were successful at generating revenue and accounted for 99.4% of the total cumulative revenues generated by the startup group. By 1989, seven of the world OEM/PCM market's ten largest firms were spin-outs. Table 1 provides our updated list of spin-outs. Our data show that after 1989, only five spin-outs and two non-spin-outs entered. This implies that Christensen's detailed analysis describes the vast majority of the entrants.

Spin-outs were an important source of entry, but were they imitators? Did spin-outs imitate firm-specific know-how of their former employer, as in our model, or did they simply learn industry-specific know-how?[2] The *Disk/Trend Report* describes several examples of firm-specific technical know-how being imitated. For example, founders of Amcodyne and Areal Technology learned how to make high areal density drives from their parent firms; founders of Dastek used thin film head technology after learning from IBM; and the founders of Tecstor modelled their drives after those of their parent firms.

[2] Alternative models from the labor economics literature may provide other possible explanations of spin-out formation. Our model is similar to a stepping-stone mobility model: an agent works at one firm, acquiring skills that allow him to move up the career ladder, possibly at another firm. Alternatively, matching models imply that employee departures occur because of a bad match. In such a model, there would be no connection between the parent firm's know-how and the spin-out's know-how.

TABLE 1 **Spin-Outs, Parents, Founding Years, and Life Spans**

Spin-Out	Parent(s)	Founding Year	Life Span
International Memories	Memorex	1977	8, Exited
Micropolis	Pertec	1977	19, Acquired
Dastek	IBM	1978	3, Acquired
Priam	Memorex	1978	12, Exited
Irwin International Industries, Inc.	Sycor	1979	3, Acquired
Seagate	Shugart Associates	1979	18, Still Active
Computer Memories	Pertec	1980	6, Exited
Ibis	Burroughs, Memorex	1980	10, Exited
Miniscribe	Storage Technology Corp.	1980	10, Acquired (by Maxtor)
Quantum	Shugart Associates	1980	17, Still Active
Rodime	Burroughs	1980	11, Exited
Rotating Memory Systems	Shugart Associates, Memorex	1980	2, Acquired
Amcodyne	Storage Technology Corp.	1981	5, Acquired
Atasi	International Memories	1981	6, Acquired
Evotek	Memorex, Data General	1981	2, Exited
Tecstor	Microdata	1981	6, Acquired
Applied Information Memories	Ibis	1982	3, Exited
Cogito	IBM	1982	6, Exited
Maxtor	Quantum	1982	14, Acquired
Microcomputer Memories	Alpha Data	1982	5, Exited
Microscience International	Datapoint	1982	10, Exited
Syquest	Seagate	1982	15, Still Active
Vertex Peripherals	Shugart Associates	1982	3, Acquired (by Priam)
Lapine	Irwin International	1983	4, Exited
Tulin	Ampex, Qume	1983	5, Exited
Epelo	Atasi	1984	1, Exited
Josephine County Technology	Tandon	1984	4, Exited
Micro Storage Corp.	Syquest	1984	2, Exited
Peripheral Technology	Computer Memories	1985	2, Acquired
Brand Technologies	Computer Memories	1986	6, Exited
Conner Peripherals	Seagate, Miniscribe	1986	10, Acquired (by Seagate)
PrairieTek	Miniscribe	1986	5, Exited
Comport	Lapine	1987	3, Exited
Kalok	Lapine	1987	7, Acquired
Areal Technology	Maxtor	1988	3, Acquired
Ecol.2	Areal Technology	1990	1, Exited
Integral Peripherals	PrairieTek	1990	7, Still Active
Orca Technology	Maxtor, Priam	1990	2, Exited
MiniStor	Maxtor	1991	4, Exited
Gigastorage International	Aura Associates	1993	4, Still Active

The exit date is the date the firm stops manufacturing and selling new drives. Spin-outs either exit through failure (denoted by exited in the life span column), are acquired (denoted by acquired), or are still active as of 1997 (denoted by still active). If the firm was acquired by another spin-out, we note the acquiring firm.

Know-how associated with entering new diameters early was also imitated. Table 2 lists early movers by diameter. Almost all of the firms listed are either spin-outs, parents, or both, with the exception of BASF, New World Computer, and Control Data.[3] Many of the firms are related to each other. Table 3 lists the spin-outs from early-mover parents along with whether the spin-out was an early mover and, if so, in which diameter. From Table 3, the probability that a

[3] Many of these firms were extremely successful. International Memories, the first mover in 8″ drives, became one of the most prominent OEM manufacturers in the early 1980s. Seagate, the first mover in 5.25″ drives, rapidly became the most prominent OEM firm and continued to hold this position as of 1997.

TABLE 2 Early Movers, by Diameter[a]

Diameter	Early Mover	Introduction Date
8″	BASF	Q4, 1979
	IBM	Q1, 1979
	International Memories	Q1, 1979
	Micropolis	Q4, 1979
	New World Computer	Q3, 1979
	Pertec	Q4, 1979
	Shugart Associates	Q4, 1979
5.25″	Computer Memories	Q2, 1981
	International Memories	Q1, 1981
	New World Computer	Q3, 1980
	Rodime	Q2, 1981
	Rotating Memory Systems	Q2, 1981
	Seagate	Q3, 1980
	Tandon	Q4, 1980
3.5″	Control Data	Q3, 1983
	Microcomputer Memories	Q1, 1984
	Microscience International	Q2, 1984
	Rodime	Q3, 1983
2.5″	PrairieTek	Q4, 1988
1.8″	Integral Peripherals	Q3, 1991

An early mover is defined to be a firm that introduces a drive in the diameter within three quarters after the first introduction. The introduction date is the date the product was first shipped. Announced products that were still in the development stage, and had not shipped, are not included.

[a] Firms are in alphabetical order in each category.

randomly selected spin-out from an early-mover parent is an early mover is $5/15 = .33$. Of the 177 firms that were not spin-outs from early-mover parents, only 12 were early movers, resulting in a probability of .068. The two probabilities differ substantially, and the difference is significant at the 1% level: the t statistic is 3.5 and the critical value is 2.33.[4]

TABLE 3 Imitation of Early-Mover Know-How, 1977–1997

Early-Mover Parent	Spin-Out	Is the Spin-Out an Early Mover?
Computer Memories, 5.25″	Brand Technologies	NO
	Peripheral Technology	NO
IBM, 8″	Cogito	NO
	Dastek	NO
International Memories	Atasi	NO
Pertec, 8″	Computer Memories	YES, 5.25″
	Micropolis	YES, 8″
PrairieTek, 2.5″	Integral Peripherals	YES, 1.8″
Seagate, 5.25″	Conner Peripherals	NO
	Syquest	NO (but was the first mover in 4″ removable cartridge drives)
Shugart Associates, 8″	Quantum	NO
	Rotating Memory Systems	YES, 5.25″
	Seagate	YES, 5.25″
	Vertex Peripherals	NO
Tandon, 5.25″	Josephine County Technology	NO

[4] If Syquest (a spin-out of Seagate) which introduced the small disk cartridge drive, is included as an early mover,

Other types of know-how related to product reliability, low cost, and marketing, which cannot be measured using our data, also appear to have been imitated. Conner Peripherals, Seagate, and Quantum are prominent examples of spin-outs with strengths in these areas whose parents had similar strengths.

In some cases, spin-outs were both imitators and innovators. A particularly striking example of this is that the first firms to introduce the major new diameters were all spin-outs: International Memories, Seagate, Rodime, PrairieTek, and Integral Peripherals. Christensen points out that it may have been easier for spin-outs to find new customers, convince them to buy new drives, and maintain focus on a new, small market because spin-outs did not face the same opportunity costs as their larger parents who were focused on existing markets.

3. The model

■ The model captures salient features of the rigid disk drive industry by incorporating a specific mechanism for imitation: employees may learn their employer's technological know-how and use it to start their own firm. The model allows for rapid improvements in production technologies and the existence of a wide range of technological capabilities. We simplify the exposition by anticipating some of the features of the equilibrium. Formal details are provided in the online Appendix.

The model describes the evolution of a single industry in a discrete-time, infinite-horizon environment.[5] There is a continuum of *ex ante* homogeneous, infinitely lived agents who are potentially in the industry at any time t. Each agent has one of H levels of technological know-how, given by $\theta \in \{\theta_1, \ldots, \theta_H\}$, where $H \geq 3$.[6] The distribution of know-how at time t is given by a vector, $\mu_t = (\mu_t^1, \ldots, \mu_t^H)$, where μ_t^i is the fraction of agents at time t with θ_i; $\Sigma_{i=1}^H \mu_t^i = 1$ and the initial distribution μ_0 is given. Having higher know-how is analogous to having more or better knowledge.

At the beginning of each period, an agent observes his level of know-how and the level of know-how of all other agents. Each period, each agent decides whether to work outside the industry, work in the industry as a researcher at an existing firm, or operate a firm in the industry. An agent who works outside the industry receives a wage w^0, and his know-how does not improve. The outside wage is constant over time. We assume that demand for the industry's good is small relative to the potential number of agents in the industry. This implies that for all possible distributions of know-how, there are always some agents who choose to work outside the industry in equilibrium.

Agents who work as researchers may imitate their employer's technology but cannot innovate, while agents who operate firms may innovate by hiring researchers but cannot imitate. Thus, an agent can improve his know-how by either innovation or imitation, but not by both. Researcher imitation is simple: a researcher learns her employer's know-how with probability λ and can use it in the following period. For simplicity, a researcher's ability to learn her employer's know-how is independent of her own level of know-how. To simplify the exposition, we assume that a researcher will never work for a firm with a lower level of know-how than her own. In the Appendix we confirm that such an event never occurs in equilibrium.[7]

Firms innovate by hiring researchers. Firms differ only by the know-how of their founders: a firm's know-how is identified with the know-how of its owner-manager. The probability that a firm will improve its know-how from its current level, θ_f, to a new level, θ_j, given its number of

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the point estimates become more compelling. Syquest is excluded because our test includes only early movers in the main diameters.

[5] This model could be incorporated into a general equilibrium model, as in Mitchell (1999), but doing so is not necessary for our purposes.

[6] Note that with only two levels, the wage structure and industry evolution are not as interesting. This model can easily accommodate a continuum of levels. For the more general version of this model, please see Franco and Filson (2000).

[7] We show that each period there is a critical value of know-how such that any agent with know-how below the critical value either works outside or as a researcher, and any agent above the critical value operates a firm. This implies that no researcher works for a firm with lower know-how.

researchers employed, L^f, is given by $\psi(j, L^f, f)$. It is *not* dependent on the current distribution of agents, μ_t, nor on the type of researchers the firm hires. In other words, all agents are identical in their research capabilities. The properties of ψ are

(i) Innovation is not guaranteed: $(\psi(f, L^f, f) > 0)$.

(ii) Innovation is costly: $(\psi(f, 0, f) = 1)$.

(iii) There is no forgetting: $(\psi(j, L^f, f) = 0$ if $j < f)$.

(iv) Increasing effort and know-how improves prospects: (If $j \geq i$, and $L^j \geq L^i$, then $\sum_{k=1}^{f} \psi(k, L^j, j) \leq \sum_{k=1}^{f} \psi(k, L^i, i), \forall f)$.

(v) $\psi(j, L^f, f)$ is a strictly increasing and strictly concave function of L^f for all levels of know-how, where $j > f$.

The first four assumptions are similar to those of Jovanovic and MacDonald (1994a), but the imitative possibilities are suppressed; incumbents cannot learn the know-how of other incumbents. This isolates the mechanism through which imitation occurs. The final condition on the innovation technology guarantees that firms with the same know-how will choose to hire the same number of researchers (expend the same innovative effort) given the same distribution of know-how.

The evolution of the industry's know-how depends on the actions of the agents in the economy. The know-how of the agents who work outside the industry is unchanged. In the case of agents who work as researchers within the industry, the fraction $1 - \lambda$ of these agents who fail to imitate are left with their previous level of know-how, while λ of these agents learn their employers' know-how. Finally, the entrepreneurs affect the distribution given their choice of how many researchers they hire. Given this period's distribution of know-how, μ_t, the following period's distribution of know-how is $\Phi(\mu_t)$. This distribution is explicitly described in the online Appendix.

□ **The agent's complete problem.** An agent who works as a researcher must decide which firm to work for. For the firm, the type of researcher does not matter, at least in terms of research productivity. All researchers are assumed to be identical in the innovation production function, and firms differ only by the level of know-how of their founder. A researcher with know-how θ_r who works for a firm with know-how θ_f receives a wage $w_t(\theta_r, \theta_f)$. Note that the wage is written to allow for dependence on both the firm's know-how as well as the researcher's. This allows for the possibility that agents with lower levels of know-how may value working as researchers more than those with higher levels of know-how. However, in equilibrium, the wage depends only on the firm's level of know-how and the distribution of know-how.

If the agent chooses to operate a firm, then the firm is characterized by its owner-manager's level of know-how. There are no sunk costs associated with destroying or creating firms. The firm's choice variables are given by the vector (q_t, ℓ_t), where q_t is the quantity produced and ℓ_t is the number of researchers hired. Both depend on the distribution of know-how as well as the owner-manager's level of know-how.[8] Note that firms may fail if unsuccessful at innovating over time, and their founders may choose to work either as researchers or in the outside option. Firms produce a homogeneous product and face an inverse demand curve, $D(Q_t)$, where Q_t is the aggregate quantity produced in the industry. For simplicity, we assume that the inverse demand function is constant over time.

The static profits of a firm operated by an agent with know-how θ_f at time t is given by $\pi_t(\theta_f) = \max_q \{p_t q_t(\theta_f) - c(q_t(\theta_f), \theta_f)\}$, where p_t denotes the price of the good produced by the industry, which is determined, in equilibrium, by the distribution of know-how and the inverse demand curve. The firm faces two costs, those associated with the production of the good and those associated with innovation. The firm's cost function for production, $c(q_t, \theta_f)$, satisfies the

[8] In the empirical section, we use a measure of quality to capture differences in know-how; q can be interpreted in terms of quality units, instead of simple output.

following standard conditions: $c(0,\theta) = 0$, $dc(0,\theta)/dq = 0$, $dc(q_t,\theta)/dq_t > 0$ for $q_t > 0$, $dc(q_t,\theta)/dq_t dq_t > 0$, $dc(q_t,\theta)/d\theta < 0$, and $\lim_{q_t \to \infty} dc(q_t,\theta)/dq_t = \infty, \forall \theta \in \Theta$. The fraction of researchers with know-how θ_i who work for firm owners with θ_j is given by ℓ_t^{ij}. Since the researchers of all types are homogeneous in terms of their output, the total innovative effort by a firm of type θ_f is $\sum_{r=1}^{H} \ell_t^{rf} = L_t^f$. The cost to a firm with θ_f of hiring researchers with θ_r is the product of the number of researchers of that type a firm hires, ℓ_t^{rf}, and the wage rate paid by the firm, $w_t(\theta_f, \theta_r)$. The total cost of innovation is the sum across all possible researcher types.

In equilibrium, no researcher works for a firm with a lower level of know-how. Under this condition, the agent's value function is given by a solution to the functional equation

$$v_t(\theta_i) = \max \Bigg\{ w^0 + \beta v_{t+1}(\theta_i),\quad \max_{f \in \{i,\dots,H\}} \{w_t(\theta_i,\theta_f) + \beta[\lambda v_{t+1}(\theta_f) + (1-\lambda)v_{t+1}(\theta_i)]\},$$
$$\max_{\ell} \left\{ \pi_t(\theta_i) - \sum_{r=1}^{H} \ell^{ri} w_t(\theta_r, \theta_i) + \beta \sum_{j=1}^{H} v_{t+1}(\theta_j)\psi(j, L_t^i, i) \right\} \Bigg\}, \tag{1}$$

where β is the discount factor and $v_t(\theta_i)$ is the value function of any agent with θ_i given the distribution of know-how at time t. The first branch is the value of working outside the industry. In this case, the agent's know-how is unchanged in the following period. The second branch is the value of being a researcher in the industry. Here the agent's future know-how becomes the same as that of his employer with probability λ; otherwise, her know-how remains unchanged. The last branch is the value of an incorporated agent. Here the agent's future know-how, θ', is determined by the transition function ψ, which was described previously.

□ **Equilibrium.** In equilibrium, agents optimize in deciding whether to work outside the industry, work as a researcher, or run a firm. Researchers choose which firm to work for optimally, and firms choose their output and employment levels optimally. The price of the good produced by the industry is set equal to the inverse industry demand given the industry's output. Wages set the supply of labor equal to the demand for labor. The evolution of the industry's know-how in a period is determined by which firms in the industry innovate and which researchers imitate, given that these agents are acting optimally. Finally, the aggregate allocation of agents to different occupations must be feasible. These conditions are described formally in the online Appendix. In equilibrium, firms are indifferent between individual researchers, researchers are indifferent between potential employers, and the wage is independent of the researcher's know-how.

□ **Optimality of the competitive equilibrium.** The proof proceeds by first showing that the competitive equilibrium aggregate allocations are the same as those generated by a single, price-taking firm that owns all the assets in the economy, where these assets are simply the know-hows of all of the agents. This is proved by showing that the marginal costs and benefits are the same in both cases. Of course, while the aggregate allocations are the same in both cases, the individual choices may not be. For example, an individual agent may be indifferent between working for any one of the firms with positive demand for researchers and working outside the industry. Where such an agent chooses to work is not important from a welfare perspective; only the aggregate allocation of agents to positions matters. The second step in the proof follows Stokey, Lucas, and Prescott (1989) by showing that the conditions that satisfy the single-firm problem are equivalent to those that satisfy the welfare-maximizing planner's problem. Since the competitive equilibrium and the single-firm equilibrium are also equivalent, the competitive equilibrium is optimal.[9] Thus, we have the following.

Proposition 1. The competitive equilibrium is optimal.

[9] Results developed by Jovanovic and Rosenthal (1988) establish that equilibrium exists, because there is no aggregate uncertainty.

Interestingly, the optimality of the competitive equilibrium does not depend on the value of λ, but the probability of not imitating is a social cost, since this slows the diffusion of knowledge. Given the option, the social planner would choose to set λ equal to one to eliminate this social cost.

The intuition behind Proposition 1 is as follows: Given that firms cannot imitate, the only potential externality in this market is from imitation by researchers. However, in equilibrium, researchers "pay" for the possibility of imitating their employer's know-how by accepting lower wages. Thus, the externality is internalized, and the competitive equilibrium is optimal.

To see why researchers "pay" for the opportunity to imitate, note that if agents did not value the future or could not imitate, all firms would pay the same wage, and this wage would equal the wage outside the industry. As long as agents value the future and can imitate, the equilibrium wages paid by more technologically advanced firms are lower than those paid by the less technologically advanced firms, and all firms with know-how worth imitating pay a wage below the wage outside the industry. The difference between the equilibrium wage a firm offers and the outside wage is determined by the difference between the expected present discounted value of having imitated the firm's know-how and the expected present discounted value of the agent's original level of know-how. Agents who work as researchers are willing to receive a lower wage for working at a firm with better know-how, because the lower wages paid by firms with higher know-how is compensated for by the future return. Firms with the best technology offer the highest return to their employees in the future.

Unfortunately, data on wages within the hard drive industry are unavailable to test this implication. However, some antecdotal evidence from both the hard drive industry and the semiconductor industry supports this implication of the model. Our results are also consistent with recent work by Moen (2000), who finds that members of technical staff in R&D-intensive firms pay for the knowledge they accumulate on the job.

□ **Firm generation and survival.** In this subsection, we consider the implications of the model for spin-out survival and which firms will generate progeny. In equilibrium, there is a critical value, θ_t^C, such that any agent with know-how greater than this critical value operates a firm. Agents with know-how θ_t^C are indifferent between running a firm and not, and agents with know-how below θ_t^C either work as researchers or work outside the industry. As the distribution of know-how improves through innovation and imitation, the critical level of know-how required to run a firm rises. Given this, agents who cannot profitably run firms today and do not improve their know-how cannot profitably run firms tomorrow.

Given that any agent who does not become an entrepreneur or who does not learn her employer's know-how does not become an entrepreneur in the future, and given that these agents are homogeneous in terms of research output, the value function is constant for any level of know-how below the critical value. There is only one cutoff in equilibrium: that which distinguishes which agents will operate firms and which will not. Since the cost of production and innovation is decreasing in technical know-how, the value function is increasing in the level of know-how for those with know-how above the cutoff. Thus, the value function is constant for levels of know-how at or below θ_t^C, and increasing for levels of know-how above θ_t^C.

Our proofs proceed under the assumption that the price never rises in equilibrium: $p_t \geq p_{t+1}$ for all t. While there is no proof that the price always falls, it seems natural to conjecture that in a competitive model where the evolution of the industry is driven by cost reduction, the price tends to fall and never rises. Further, when we compute the equilibrium of the model numerically, as in Section 4, the price does not rise from period to period. Given this, it is clear that it is possible to choose functional forms and parameter values so that price never rises in equilibrium.

The next three results provide the hypotheses that are tested with the data from the rigid disk drive industry in Section 5.

Proposition 2. In period t, if there is any firm i with $\theta_i < \theta_{t+1}^C$, none of its researchers run firms in period $t+1$. For any firm j with $\theta_j > \theta_{t+1}^C$, each of its researchers will run firms in period $t+1$

with probability λ. For any firm k with $\theta_k = \theta^C_{t+1}$, each of its researchers run firms in period $t + 1$ with a probability of at most λ.

Proposition 2 implies that firms with greater technological know-how are more likely to generate spin-outs. Those with know-how below next period's cutoff generate no spin-outs. In the case where $\theta_i = \theta^C_{t+1}$, it may not be the case that all successful imitators will run firms. It may be the case that only some of the agents with θ^C_{t+1} will operate firms in equilibrium. However, agents with θ^C_{t+1} will be indifferent between operating a firm and working.

Now assume that (vi) $\psi(j, L^f, f)$ is multiplicatively separable in L^f and f: $\psi(j, L^f, f) = F(j \mid f)G(L^f)$, where $G(L^f)$ is the probability that the firm obtains a new level of know-how given its innovative effort and $F(j \mid f)$ is the probability of drawing θ_j when the firm has θ_f, given the draw occurs.

Proposition 3. The probability that an agent who currently operates a firm will continue to operate a firm in the following period is weakly increasing in his know-how.

Note that even though the likelihood of survival is increasing in know-how, leapfrogging is still possible in the model because of the stochastic learning technology. Leapfrogging is discussed further in Section 4.

Finally, the probability of a spin-out surviving beyond its first year is increasing in its parent's know-how. That is:

Corollary 1. The probability that an agent who imitates his former employer's technology and starts up a firm will operate a firm in the following period is weakly increasing in his former employer's know-how.

This provides a basis for predicting which spin-outs will survive and which will not.

4. Simulation

■ In this section we simulate the model to provide an example of how innovation, imitation, and industry evolution occurs. The simulation is also useful for illustrating how the model can reconcile three facts about the disk drive industry's evolution described by Christensen (1993, 1997) and Lerner (1997). First, entry and spin-out formation peaked in the early 1980s. Second, industry profits were low in the late 1970s and later rose in the 1980s and 1990s as the market matured, even though the price per megabyte was declining. Third, during this period laggards had a systematic tendency to catch up to and occasionally surpass leaders.

Functional forms and parameter values used in the simulation were chosen to roughly match the broad trends in entry and profits in the data. Figures 1 through 8 graph various simulated series. For simplicity, there are three levels of know-how: low-tech, medium-tech, or high-tech, denoted by θ_L, θ_M, and θ_H, respectively. This isolates imitation: low-tech researchers can imitate medium-

FIGURE 1

PERCENTAGE OF AGENTS OF EACH TYPE

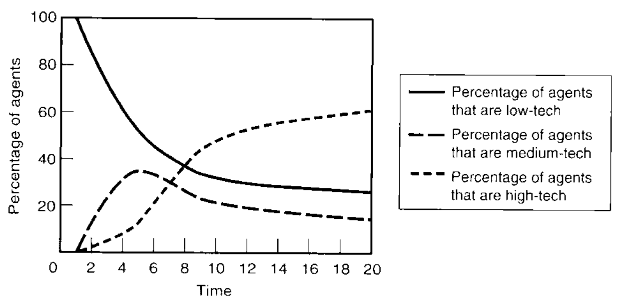
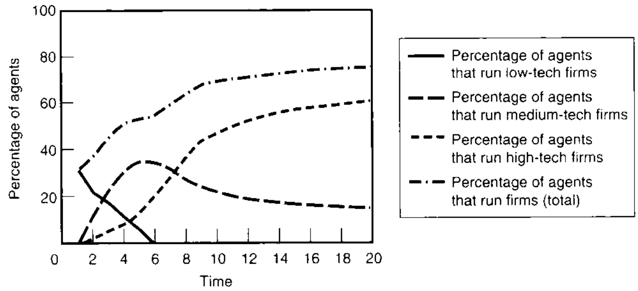


FIGURE 2

PERCENTAGE OF AGENTS WHO ARE INCORPORATED AND ARE OF EACH TYPE



tech firms, but no other imitation occurs. No agent can improve his know-how by working for a low-tech firm, and the parameter values ensure that high-tech firms do not hire researchers.[10]

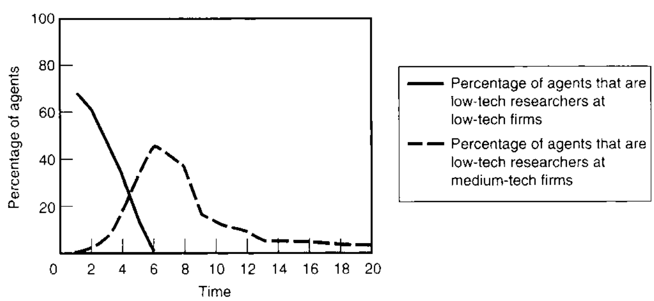
We assign the following values: $\theta_L = 1, \theta_M = 4, \theta_H = 5, w^0 = .15, \beta = .9$, and $\lambda = .1$. The production cost function is quadratic in output: $c(q;\theta) = q^2/(2\theta)$. The market demand function is linear: $Q = 2 - 2.5p$. The firm's transition function is specified as follows. Firms obtain a new θ with a probability that depends on the number of researchers they employ: $\min\{0.4\ell^{.9}, 1\}$, where ℓ is the firm's number of researchers. Low-tech firms that obtain a new θ become medium-tech agents with probability .5, become high-tech agents with probability .1, and remain low-tech agents otherwise. Medium-tech firms that obtain a new θ become high-tech agents with probability .5 and remain medium-tech agents otherwise.

Figure 2 shows that as know-how improves, net entry occurs and reaches its peak by the tenth period; this roughly matches the trend in net entry in the disk drive industry. In fact, the pattern in net entry matches that established by Gort and Klepper (1982) for new industries in general. They explain the pattern by assuming that entering firms come with knowledge from outside the industry. Our results show that such an assumption is not necessary; entering firms in our model are pure imitators. Figure 3 shows the percentage of agents that work as researchers. Low-tech researchers at medium-tech firms imitate at a rate of 10% and start up new medium-tech firms in the following period. Most spin-outs are formed in the fourth through tenth periods. These periods correspond to the early to middle 1980s, when most of the disk drive spin-outs were formed.

The simulation also matches the evolution of prices and profits in the hard drive industry. Figure 5 shows that as know-how improves, the price and average cost fall and the market quantity rises. This matches the pattern of falling cost per megabyte that occurred in the industry. We report

FIGURE 3

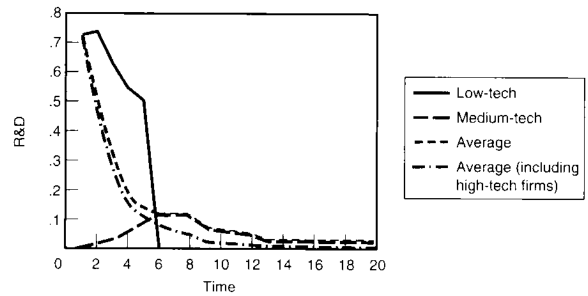
PERCENTAGE OF AGENTS WHO ARE RESEARCHERS, BY TYPE OF AGENT, AND FIRM



10 Because high-tech firms have the highest possible know-how, they have no incentive to hire researchers. However, under some parameter values equilibrium can involve all non-high-tech agents working for the high-tech firms for negative wages in order to possibly imitate the employer's technology. In this case imitation occurs, but no innovation occurs.

FIGURE 4

R&D EXPENDITURE PER FIRM



two profit series that allow for different R&D accounting methods.[11] Figure 4 shows that R&D expenditures per firm, which depend on how many researchers are employed, are initially high and fall over time. Figure 6 graphs revenue minus production costs and R&D expenses, and Figure 7 graphs revenue minus production costs. The basic pattern of rising average profits occurs in both series. Gort and Klepper (1982) claim that periods of high net entry, falling price, and rising quantity are typically associated with innovations generated outside the industry. The simulation demonstrates that this is not always the case; all of the entrants are spin-outs that obtain their know-how from their parent firms.

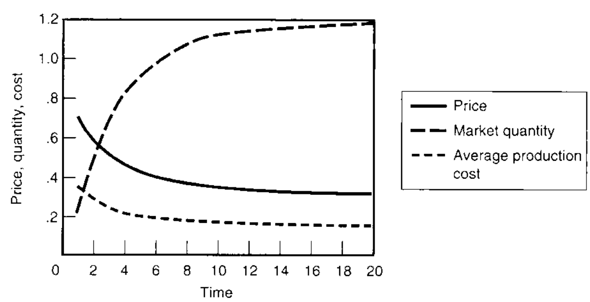
The results also match the pattern of laggards occasionally surpassing the leaders. Low-tech firms become high-tech at faster rates than medium-tech firms do in periods 2 and 3. This does not always occur; in periods 4 and 5, medium-tech firms innovate at faster rates. Leapfrogging can occur in the model because the firm's learning technology is stochastic and depends on investment levels: if low-tech firms invest much more than medium-tech firms, then they innovate at higher rates. Low-tech firms have higher costs of innovation because they must pay higher wages to researchers but may have higher expected benefits, because in comparison to medium-tech firms their values are much lower than those of high-tech firms. This can be seen in Figure 8, which shows the value of agents by type. The difference in value between low-tech and medium-tech agents is always larger than that between medium-tech and high-tech agents.

5. The rigid disk drive industry

■ **The data.** The main data source is the *Disk/Trend Report* on Rigid Disk Drives (Porter, 1977–1997). The dataset contains 192 firms, 1,190 firm/year observations, and 11,644 model/year

FIGURE 5

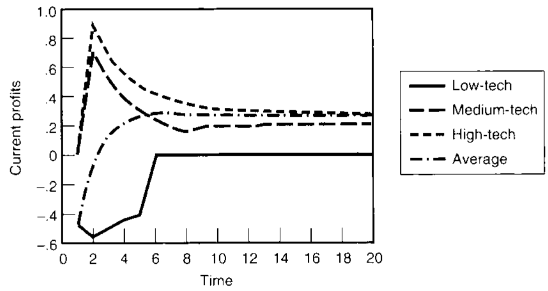
PRICE, MARKET QUANTITY, AND AVERAGE PRODUCTION COST



[11] Much R&D activity in firms in rapidly evolving industries is not separated from other costs; every employee may play a role in improving products and processes. Therefore, reported profits likely include some of what is R&D in the model as part of production costs.

FIGURE 6

CURRENT PROFITS PER FIRM (INCLUDES R&D)



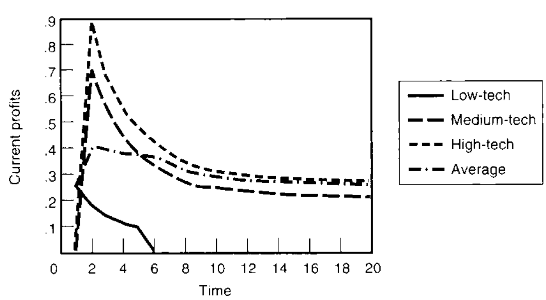
observations. The data include product characteristics and introduction dates. Annual sales of disk drives are reported for several firms.[12] Information on the backgrounds of founders of new firms is provided, and historical information and recent news are summarized for each firm. To determine spin-out/parent relationships, the histories from the *Disk/Trend Report* were supplemented with company press releases and articles provided by James Porter, the editor of the *Disk/Trend Report*. Other sources include the *Directory of Corporate Affiliations*, the *International Directory of Company Histories*, and Christensen (1993).

There are 40 cases of one or more employees leaving one or more rigid disk drive manufacturers to found a new firm in the period 1977–1997. Table 1 sorts the spin-outs by year of entry and lists the parent firms, the founding year of the spin-out, and the spin-out's life span and mode of exit.[13] To determine the parent firms, we focus on the background of the founders and not on other employees, for which data are unavailable. The implicit assumption is that founders determined the know-how of the startup; evidence from company press releases and the *Disk/Trend Report* supports this assumption.

To test the model's implications for spin-out generation and firm survival, we use the available data to construct two measures of know-how. *Technical know-how* measures the firm's technical expertise using areal densities. The areal density is the main measure of drive quality; it measures how much information can be stored on each square inch of disk. The areal density of the firm's best drive in each diameter in each year is divided by the highest areal density in that diameter in that year to generate a measure of the firm's know-how in each diameter relative to the best

FIGURE 7

CURENT MARKET PROFITS PER FIRM (EXCLUDES R&D)

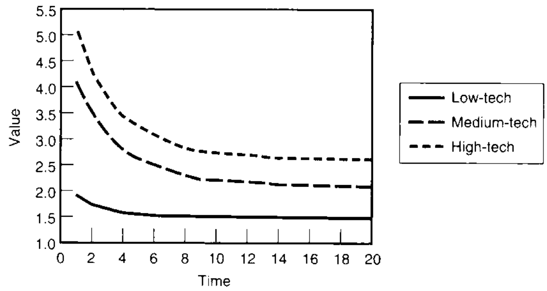


[12] Sales of other products, including licenses and disk drive components, are not included in the measure of disk sales. Only sales of drives are counted.

[13] The data start in the late 1970s, once the industry was into its takeoff stage. All of the noncaptive parent firms of the early startups were also spin-outs (Christensen, 1993). Memorex, Pertec, and Storage Technology Corporation were IBM spin-outs; Shugart Associates was a Memorex spin-out; and Tandon was a Pertec spin-out.

FIGURE 8

VALUE OF EACH TYPE OF AGENT



available know-how in that diameter.[14] Then this measure is averaged across diameters to obtain a single measure of the firm's technical know-how in each year. The firm-level measure is necessary because the theoretical results pertain to firm-level decision making.[15] *Early mover know-how* is a dummy variable for firms that introduced a drive of a new diameter within the first year that drives of that diameter were shipped. Early mover know-how is a proxy for the product design, product reliability, and marketing know-how associated with designing, manufacturing, and marketing new drives. Only the major diameters introduced in 1977–1997 are considered: the 8″, 5.25″, 3.5″, 2.″, and 1.8″ drives.

Intellectual property rights over know-how are implicitly assumed to be weak in the model. Empirically, institutional barriers to imitation appear to be low in the disk drive industry. Lerner provides evidence that patents were not widely used to protect key aspects of drive technology, and examples in the *Disk/Trend Report* show that when patents were used, licensing was widespread. Further, covenants not to compete and trade secret laws were largely ineffective. Most of the firms in this study were located in California, where covenants not to compete were prohibited by law and not enforced by the courts. Trade secret laws did not create much of an employee mobility barrier because of large contract negotiation costs, difficulties with enforcing the laws, and the Silicon Valley culture.[16]

Spin-out formation. According to the model, spin-outs come from firms with relatively high know-how. This hypothesis is tested using several probit models, where the dependent variable is one if the firm generates a spin-out in the current year. In our theoretical model, the probability that a firm generates a spin-out in period t depends only on the firm's know-how in period $t-1$ and the distribution of know-how. Therefore, the independent variables are lagged values of technical know-how and early-mover know-how. We use year dummies to account for changes in the distribution of know-how from year to year. Year dummies capture all changes in industry-level variables from year to year, and in the model, all industry-level changes depend on changes in the distribution of know-how. We use 1983 as a base year. Table 4 reports summary statistics and Table 5 reports the estimation results.

The list of spin-out parents in Table 1 includes many of the most successful disk drive firms. If success was due to "know-how," however defined, then these firms clearly had high know-how. Thus, even without using explicit know-how measures, the hypothesis appears to have some support. The statistical analysis confirms this impression and is presented in Table 5. In equation 5(a), both know-how coefficients are positive and significant. This supports the hypothesis. The magnitude of the effects is quite large: at the mean values of the data, obtaining

[14] Only drives that have been shipped and produced are used in these calculations. We assume that improvements in technical know-how are rapidly embodied in new products. Lerner (1997) argues convincingly that this is the case in the disk drive industry.

[15] Lerner treats each diameter separately in most of his analysis but reports some results using this average measure.

[16] Gilson (1999), Hyde (2003), and Saxenian (1994) discuss covenants not to compete and trade secret law in the Silicon Valley environment.

TABLE 4 Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Cases
Technical know-how	.44	.25	.0084	1.00	1,039
Lagged technical know-how	.45	.24	.0084	1.00	877
Early-mover know-how	.15	.36	.00	1.00	1,190
Lagged number of drives	11.31	15.06	1.00	119	886
Lagged sales growth	.21	.65	−2.00	2.00	846
U.S. firm dummy	.62	.49	.00	1.00	1,190
Spin-out generation dummy	.032	.18	.00	1.00	1,190
Survival dummy	.91	.29	.00	1.00	1,172

Definitions of technical know-how, early-mover know-how, and sales growth are provided in the text. Technical know-how and lagged technical know-how range from 0 to 1. Early-mover know-how is a dummy variable. Lagged sales growth ranges from −2 to 2. Lagged number of drives measures the number of drives produced by the firm in the previous period. The U.S. firm dummy takes the value 1 if the firm is an American firm, and 0 otherwise. The spin-out generation dummy takes the value 1 if the firm generates a spin-out in the current period, and 0 otherwise. The survival dummy takes the value 0 if the firm exits through failure in the following period, and 1 otherwise.

early-mover know-how raises the probability of generating a spin-out from .13 to .19, and raising technical know-how from .25 to .75 raises the probability of generating a spin-out from .11 to .18. In unreported estimates, the robustness of these results was checked by limiting the sample to U.S. firms. Only U.S. firms generated spin-outs in the disk drive industry; institutional differences between the United States and Japan, the country in which most foreign firms were based, possibly made spin-out generation more likely in the United States. The results were essentially unchanged.

Equation 5(b) is similar to equation 5(a) but includes two additional control variables: lagged sales growth and the lagged number of drives produced. Sales growth is computed as $g_t = (s_t - s_{t-1})/[(s_t + s_{t-1})/2]$, where g_t denotes the growth rate and s_t denotes firm sales in period t. This formula ensures that g_t is finite if either s_t or s_{t-1} is zero. For new entrants that have zero sales in two adjacent periods, g_t is set equal to zero. If a spin-out has two parents, the average of the parents' sales data is used.

Including these variables allows us to test two alternative explanations for spin-out formation. Lagged sales growth allows us to test whether spin-outs formed as a result of employee exit from a failing firm. This test is partly motivated by a few cases in Table 1 in which spin-out formation occurred when a once prominent parent suddenly declined. In 1985–1986, Computer Memories lost its largest customer when IBM decided to supply more of its needs in-house. As Computer Memories declined, employees left and two spin-outs were formed: Peripheral Technology and Brand Technologies. In another case, when Lapine failed after its brief success, employees abandoned it and founded new firms: Comport and Kalok. The learning described by the model may still have been present, but the departure was partly forced rather than entirely voluntary. The coefficient on lagged sales growth is positive, which suggests that spin-outs are more likely to come from firms that are doing well in the market rather than those that are retrenching or declining.

The lagged number of drives is a proxy for firm size. A simple hypothesis about spin-out generation is that spin-outs are more likely to come from larger firms simply because larger firms have more employees who can leave. The result does not support this simple hypothesis; the coefficient on lagged number of drives is negative and insignificant. We also checked lagged sales as a proxy for firm size and obtained the same result: the coefficient was negative and insignificant and the other results were unchanged. The robustness of all of our results was checked by limiting the sample to U.S. firms; the results were unaffected.

Firm survival. The second implication of the model is that the probability of a firm surviving until the following period is increasing in its current know-how. This hypothesis is tested using several probit models. If a firm exits in period t because it is acquired, the exit year is treated as censored; only failures count as exits.

Table 6 reports the estimation results. In equation 6(a) both know-how coefficients are

TABLE 5 **Probability of Generating Spin-Out as Function of Know-How. Probit Model Dependent Variable: Spin-out Generation Dummy**

Variable	Equation 5(a) Coefficient	Equation 5(b) Coefficient
Constant	−2.67***	−2.58***
	(.44)	(.45)
Lagged technical know-how	1.12***	1.08***
	(.37)	(.40)
Early-mover know-how	.49**	.47**
	(.19)	(.21)
Lagged sales growth	—	.12
		(.15)
Lagged number of drives	—	−.0096
		(.0080)
YR1978	.44	.57
	(.57)	(.57)
YR1979	.15	.077
	(.61)	(.62)
YR1980	.82*	.80*
	(.49)	(.49)
YR1981	.84*	.85*
	(.48)	(.48)
YR1982	.83*	.81*
	(.48)	(.48)
YR1984	.25	.22
	(.51)	(.51)
YR1985	−.14	−.13
	(.59)	(.59)
YR1986	.32	.37
	(.50)	(.50)
YR1987	−.083	−.037
	(.58)	(.59)
YR1988	−.059	.053
	(.60)	(.62)
YR1990	.67	.89*
	(.49)	(.51)
YR1991	−.12	.17
	(.59)	(.62)
YR1993	.0013	.50
	(.60)	(.66)
Number of observations	673	556
Log-likelihood	−117.03	−112.19

Standard errors in parentheses.

* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

For the year dummies, 1983 is the base year. We follow standard practice and exclude years where no firms form spin-outs (in which case all dependent variables are 0 and can be explained perfectly by the year dummy) from the analysis.

positive. This supports the hypothesis. At the mean values of the data, obtaining early-mover know-how raises the probability of surviving from .78 to .82, and raising technical know-how from .25 to .75 raises the probability of surviving from .75 to .84. The results are similar if we limit the sample to U.S. firms, but for brevity we do not report these results. Equation 6(b) reruns 6(a) including only spin-outs and shows that the results are similar. In the theoretical model, spin-outs

TABLE 6 **Probability of Surviving to Following Period as Function of Know-How. Probit Model Dependent Variable: Survival Dummy**

Variable	Equation 6(a) Coefficient	Equation 6(b) (Spin-outs only) Coefficient
Constant	.96***	.76
	(.25)	(.59)
Technical know-how	.99***	1.46**
	(.25)	(.61)
Early-mover know-how	.27	−.029
	(.20)	(.29)
YR1978	.50	
	(.50)	
YR1979	.11	
	(.38)	
YR1981	.81*	
	(.48)	
YR1982	.30	
	(.35)	
YR1984	−.21	−.10
	(.30)	(.62)
YR1985	−.17	−.11
	(.31)	(.63)
YR1986	−.37	−.22
	(.30)	(.71)
YR1987	−.010	−.013
	(.33)	(.66)
YR1988	.046	.032
	(.33)	(.73)
YR1989	−.013	−.21
	(.33)	(.65)
YR1990	−.17	−.60
	(.32)	(.64)
YR1991	−.69**	−.81
	(.29)	(.62)
YR1992	−.61**	−.70
	(.31)	(.66)
YR1993	−.72**	
	(.31)	
YR1994	−.68**	−.32
	(.33)	(.74)
YR1996	−.39	−.28
	(.37)	(.78)
Number of observations	918	
Log-likelihood	−301.41	

Standard errors in parentheses. Dependent variable is 0 if firm exits through failure in the following period, and 1 otherwise.

When year dummies are included, 1983 is the base year. We follow standard practice and exclude years where no firms exit (in which case all dependent variables are 1 and can be explained perfectly by the year dummy) from the analysis.

* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

are assumed to evolve according to the same transition rules as other firms; equation 6(b) shows that this assumption is reasonable.

Spin-out survival. The final implication states that a spin-out's likelihood of surviving beyond its first period is increasing in its parent's know-how. Unfortunately this does not lead to an

TABLE 7 **Summary Statistics on Spin-Outs**

	Mean	Standard Deviation	Minimum	Maximum	Cases
Spin-out life span	6.60	4.80	1.00	19.00	40
Parent technical know-how	.57	.28	.053	1.00	34
Average parent technical know-how in 3 years surrounding spin-out's entry	.48	.23	.019	1.00	38
Parent early-mover know-how	.39	.50	.00	1.00	40
Parent sales growth in 3 years surrounding spin-out's entry	.085	.67	−1.86	1.6	38
Entrepreneur dummy	.30	.46	.00	1.00	40
Number of censored observations	19				

Parent technical know-how and average parent technical know-how range from 0 to 1. Parent early-mover know-how is a dummy variable. Parent sales growth ranges from −2 to 2. The entrepreneur dummy is a dummy variable. The censored observations are spin-outs that have either been acquired or are still active at the end of the sample.

interesting test, because all the spin-outs in the data except two survived beyond their first year. Instead, a more general hypothesis is tested: a spin-out's expected lifetime is increasing in its parent's know-how. We use duration models in which the spin-out's lifetime is a function of its parent's know-how. Table 7 reports summary statistics, and Table 8 reports the estimation results.

We obtained the best fit using a Weibull survival function of the form $\exp(-(\phi t)^{1/\sigma})$, where $\phi = \exp(-\beta' x_i)$. The resulting hazard function, which gives the probability that a firm exits given that it has survived until time t, is given by $(\phi/\sigma)(\phi t)^{(1/\sigma)-1}$. The parameters β and σ are estimated, and x_i represents firm i's parent's know-how. All spin-outs that were still alive in 1997 and those that were acquired before 1997 are treated as censored observations. While checking the robustness of the results, we estimated a Markov chain model that allowed for the two types of censoring explicitly. The results did not change: it appears that general statements about how the

TABLE 8 **Spin-Out Life Span as Function of Parent Know-How Duration Model Using Weibull Specification Dependent Variable: Spin-out's Life Span**[a]

Variable	Equation 8(a) Coefficient	Equation 8(b) Coefficient	Equation 8(c) Coefficient	Equation 8(d) Coefficient
Constant	2.61***	2.73***	2.73***	2.84***
	(.49)	(.45)	(.46)	(.46)
Parent technical know-how	−.71	—	—	—
	(.64)			
Parent early-mover know-how	.68	.78*	.66*	.79**
	(.43)	(.41)	(.40)	(.40)
Average parent technical know-how in the 3 years surrounding the spin-out's entry	—	−1.18*	−1.18*	−1.30*
		(.70)	(.72)	(.71)
Parent sales growth in the 3 years surrounding the spin-out's entry	—	—	.55*	.59**
			(.29)	(.29)
Entrepreneur dummy	—	—	—	−.31
				(.39)
Sigma	.73***	.70***	.65***	.64***
	(.22)	(.41)	(.19)	(.19)
Number of observations	34	38	38	38
Log-likelihood	−33.03	−36.20	−33.55	−33.26

[a] See Table 1. Standard errors in parentheses. The definitions of technical know-how, early mover know-how, other know-how, and the entrepreneur dummy are discussed in the text.

* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

probability of being acquired depends on know-how and our other controls cannot be made. This conclusion makes sense given the history of the industry. All types of firms have been acquired throughout the life cycle, including new small firms still in the development stage, large successful firms, and failing firms.

In equation 8(a) only the two parent know-how measures are included. The coefficient on parent technical know-how is negative, but both coefficients are insignificant. In equation 8(b), more precise estimates are obtained using a three-year average of parent technical know-how. The coefficient is still negative, while the coefficient on early-mover know-how is positive. Interestingly, spin-out survival is decreasing in parent technical know-how. However, as shown in Table 6, the probability of a spin-out surviving is increasing in its own technical know-how. The results suggest that technical know-how was more difficult to imitate than early-mover know-how. Spin-outs that came from firms with high technical know-how were less likely to imitate successfully and therefore less likely to survive, but if they were successful at learning this type of know-how, they were more likely to survive. Christensen's (1993) analysis supports this conclusion. Many of the advances that improved areal densities were extremely expensive and time-consuming to develop, and only the large established firms were successful with these development projects. New small firms that tried had an extremely high failure rate.

In equation 8(c), parent sales growth is added as an explanatory variable. As mentioned above, some spin-outs were formed when the parent was failing. The estimates of equation 8(c) show that spin-outs from failing firms were less likely to have long lives than those from growing firms. The coefficients on parent know-how do not change substantially.

Another type of spin-out formation involved entrepreneur mobility: in several cases in Table 1, one or more of the spin-out founders were also founders of the parent firm.[17] This suggests that expertise in founding startups, as well as other types of know-how, was useful. This entrepreneurial know-how is less likely to diffuse in the manner featured in the model because it is more likely to be obtained from experience at founding startups than from working for other firms. In equation 8(d), we include an entrepreneur dummy. If one of the spin-out founders was also a founder of the parent firm, this dummy takes the value of one. Interestingly, the coefficient on the entrepreneur dummy is negative. Although the estimate is imprecise, it suggests that past experience at founding startups may have a negative impact on the lifetime of a new startup. This result is similar to that documented in the PC software industry by Prusa and Schmitz (1994). This may be the case in rapidly evolving industries: past experience at founding a startup may not be as important as having the right know-how for the current environment.

6. Conclusion

■ Spin-outs are prevalent in a wide variety of industries, particularly early in the life cycle (Garvin, 1983). In order to understand the effects of this phenomenon on industry dynamics, we developed a model and tested it using data from the rigid disk drive industry, which is a generic example of a high-tech industry. The model and empirical results provide insight into the role that spin-outs play in an industry's evolution. In the model and in the data, firms with higher know-how are more likely to generate spin-outs and survive. As the model suggests, firm size is not a good predictor of spin-out generation once we control for know-how. However, while parental early-mover know-how is a good predictor of spin-out survival, as the model suggests, parental technical know-how is not; our estimates suggest that this is because technical know-how is particularly difficult to imitate.

While this article tests the model using the rigid disk drive industry, the employee mobility model is a reasonable description of other industries. The semiconductor, laser, and computer software industries all have high employee mobility (see Braun and Macdonald, 1982; SEMI,

[17] These spin-outs were Micropolis, Irwin International, Seagate, Applied Information Memories, Maxtor, Syquest, Epelo, Brand Technologies, Conner Peripherals, PrairieTek, Areal Technology, and Ecol.2. In two cases, the spin-out founder sold the parent firm before founding a new firm. In one case, a spin-out founder left a failing firm to found a new one. In the rest, the founder left a viable one.

1986; Klepper and Sleeper, 2000; and Wilson, Ashton and Egan, 1980), and these industries have evolved in a pattern similar to that of the hard drive industry.

Our results suggest that preventing employee mobility leads to inefficient resource allocation, even though employees transfer know-how between firms. In contrast to other models of diffusion, such as Jovanovic and MacDonald (1994a), the competitive equilibrium in our employee mobility model is optimal. This result establishes that the equilibria of models of diffusion with active learning can be efficient when imitation is allowed. It also suggests that public policies that affect employee mobility have important effects on firm entry and technological diffusion in industries where know-how is an important factor of production. Since social welfare is increasing with the probability of imitation, policies that limit mobility may ultimately have a detrimental effect on social welfare.

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